A Model for Range Estimation and Energy-Efficient Routing of Electric Vehicles in Real-World Conditions

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Abstract—This paper presents an integrated model for energy consumption and range estimation, capable of energy-efficient routing. This integrated model predicts the energy consumption on all road segments in the road network and applies shortest path algorithms to calculate energy-efficient routes. A temperature-dependent model of the battery internal resistance based on real-world data translates the energy consumption prediction into driving range. The graph representation of the road network is transformed from a node-based graph to an edge-based graph to allow cost allocation of one edge based on the characteristics of the preceding edge. The integrated model is used to perform an analysis of energy-efficient routes for a real-life scenario. The analysis showed that the energy-optimal route is different from the time- and distance-optimal route with energy-efficiency gains up to 37% for the chosen scenario. The energy-efficient route tends to lean toward a distance-optimal route in the case of low auxiliary consumption and to lean toward a time-optimal route in the case of high auxiliary consumption. The energy-efficient route generation is tested in real life for one case of the chosen scenario. The measured results showed a good match with the predicted values for the energy consumption with a 9% mean relative error and preserved the ranking of all routes in terms of the travel distance, travel time, and energy consumption. The proposed integrated model is a functional model for energy consumption in real-life that differentiates many energy consumption influencing factors and produces energy-efficient routes with good accuracy.

Index Terms—Electric vehicles, energy-efficient routing, energy consumption.

I. INTRODUCTION

THE Electric vehicle (EV) has great potential to reduce the impact of the transport sector on global warming by decreasing greenhouse gas emissions, particularly in combination with low emission electricity production, and to improve local air quality by not emitting tail-pipe emissions [1]. However, despite advances in battery technology and decreasing battery prices, which result in higher installed battery capacity in commercial vehicles, the EV's driving range is still low compared to its conventional technology competitor [2] and

energy consumption reported to be up to 60% higher in real-life than measured on New European Drive Cycle (NEDC) [3]–[5]. This limited battery capacity, combined with a highly variable energy consumption and limited availability of charge infrastructure, lead to range-anxiety [6]. To address the issue of range-anxiety, this paper proposes an integrated model for range estimation and energy-efficient routing. Energy Efficient routing, or E-routing, in general stands for generating energy-efficient alternative routes to travel from an origin to a destination in a road network. The calculation of the path with the lowest energy consumption is generally done by allocating an energy cost to the road segments and applying cost-optimization algorithms, generally known as shortest path algorithms (SPA). Compared to energy-efficient routing for ICE vehicles [7], energy-efficient routing for EVs apply different energy prediction models, and further differentiate themselves by the range restrictions, charging requirements and the presence of negative costs. Literature on models for energy-efficient routing generally only focuses on either the prediction of the energy consumption on road segments or making the routing algorithm computationally superior, in which case the energy prediction model and translation into driving range are often generic, serving only to illustrate the capabilities of the routing algorithm. This paper continues the work presented in [8], [9], where a data-driven energy consumption prediction for electric vehicles in real-world conditions was presented, by adding an analysis of internal losses of the battery and integrating the energy consumption as a cost function in the routing. The integrated model presented in this research is a functional, validated model for range estimation and energy-efficient routing in real-world conditions.

II. STATE-OF-THE-ART OF ENERGY-EFFICIENT ROUTING FOR ELECTRIC VEHICLES

Literature ranges from methods to generate E-routes for an individual driver [10], possibly with range restrictions and the option to charge [11], [12], to research that calculates routes to obtain network energy optima [13]. Other specific traditional cost-optimization problems such as the vehicle routing problem or travelling salesman problem, where a monetary cost-optimization of delivery problems is sought (i.e. delivery of goods, products and services to multiple costumers considering time constraints, range constraints, and operational cost), are adapted to the case of electric vehicles [14], [15] and electric vehicle fleets including charge scheduling and battery

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degradation [16]. Recently, mobility-on-demand serviced by electric vehicles has triggered routing algorithms that minimize overall trip time for all customers considering charging needs [17].

A. Shortest-Path-Algorithm

Generating cost optimal routes for single drivers are generally done by applying shortest path algorithms to a graph representation of the road network. The graph representation of the road network consists of edges (also called links) connected at vertices (also called nodes), where the edges represent road segments and the vertices represent the intersections. The edges in the graph are given a cost, and shortest path algorithms calculate cost optimal solutions between vertices in the graph. In navigation applications, the cost function is traditionally the travelled distance or travel time between vertices. In the case of E-routing, the cost between vertices is the energy consumption. SPAs are well established since the late 1950s, with the Bellman-Ford algorithm (1958) [18], Floyd-Warshall (1962) [19], and the most famous, generally applied in navigation applications, Dijkstras algorithm (1959) [20]. Both Bellman-Ford and Dijkstras expansion procedures guarantee optimal solutions, but will expand unintelligently to the full network (or a large part of the network for Dijkstra) before reaching the destination vertex with an optimal solution. Heuristic algorithms can be used to decrease the calculation time by intelligently expanding to vertices in the network in such a way that vertices, unlikely to provide the shortest path, are excluded from the expansion. The drawback of heuristics SPA is the fact that they are not guaranteed to produce optimal solutions. A literature overview of heuristic approaches to shortest path algorithms for transportation was presented in [21].

Energy-efficient routing for EVs introduces the specific challenge of the presence of range restrictions and negative edge costs, for which the Dijkstras algorithm is not suited. The Bellman-Ford algorithm can deal with negative links, yet increases computational time. It has been proposed in several publications as the shortest path algorithm for EVs [22]. Other specific shortest path algorithms for electric vehicles have been proposed and evaluated: metaheuristic approach in [12], particle swarm optimization in [23], Dijkstras algorithm with shifting technique (Johnsons) [24]. Some authors extend the SPA to include state-of-charge requirements [25].

Algorithms that provide the shortest path from any origin vertex to any destination vertex, are generally called all-pair shortest path algorithms (APSPA). APSPA can be advantageous when shortest paths must be found in real-time in large networks. By pre-calculating all-pair shortest paths, shortest paths can later be queried fast from memory. In general, shortest paths can be programmed through dynamic programming, and the established algorithms are variants to the dynamic programming structure [26].

B. Energy-Efficient Routing

A number of solutions for energy-efficient routing of electric vehicles are proposed in literature. In [27], the platform for a

route planner is presented which implements a standard route-planner in combination with an EV vehicle model, which was presented in [28]. However, this platform assumes the speed profile is known and inserted into the vehicle model. No evaluation of that proposed model was presented in [27] or found in other publications of the same authors. In [29], an energy consumption estimation model was constructed using multiple linear regression based on historical data of average speed, accelerations, road gradient and future data of the driving speed assumed to be known. The methodology applies Dijkstras algorithm to determine the most energy-efficient route on a simplified network. This methodology has an interesting structure and applies sufficient averaging to be usable for large scale, network prediction. However, only a limited number of parameters are accounted for in the linear regression model and the link with the vehicle dynamics is largely lost. Moreover, no validation and no accuracy of the proposed methodology are presented. In [30], a generic energy consumption estimation model is developed, which calculates the power requirements from the driving resistance and auxiliary consumption. The driving resistance is calculated using speed dependent functions that estimate the share of the link spent in different driving phases (i.e. cruising, acceleration, deceleration and idle) based on the historic link speed, and uses average fixed values for the acceleration and deceleration. The method was evaluated by comparing the model results with results obtained from a model developed with the Passenger and Heavy Duty Emission Model (PHEM) on real GPS measured driving patterns. However, this paper lacks an in-depth evaluation with real energy consumption data and assumes link speeds are known or extractable and is therefore not immediately usable in its current form. In [31] (and from the same author [32]), the statistical representation of traffic-, driver-, and situation-related features in speed profiles on specific road segments are correlated with the deviation from the normalized energy consumption of the respective vehicles, in order to estimate the energy consumption over a given route. A regression model estimates the energy consumption from the established most influential principle components, which themselves are predicted by historic mean values of these traffic-, driver-, and situation related features. A validated vehicle model is used to calculate the energy consumption based on real-world GPS measured driving data. Although energy-efficient routing was not discussed in this publication, the separation of trips in road segments for the energy prediction, allows for energy efficient routing. A model for energy consumption forecasting based on vehicle-, road-, traffic-, weather-, and driver profile-related parameters using a neural network was presented in [33] and extended to be applied in e-routing application by the same authors in [10], [24]. To decrease computational times associated with shortest path algorithms that can handle negative link costs such as Floyd-Warshall, the authors propose the shifting technique described by Johnson in [34]. An energy-efficient routing model for EVs based on real-time data of a local traffic center has been presented in [35]. The authors proposed an altered Bellman-Ford algorithm that can deal with time-variant, negative links and dimensionless nodes are expanded to areas of intersections

to be able to implement the dynamic traffic data. However, the presented energy estimation model is basic and few values on model accuracy are reported. Only in a limited number of publications, the energy-efficient routing has been extended to range estimation by including the battery capacity. A holistic approach towards routing for electric vehicles is presented in [11]. The authors focus on the challenges for the calculation of a route in the EV context, including the SoC and recharging requirements, and propose approaches to deal with these. However, very little information on the energy estimation model and its input drive cycles is provided, nor does it contain an implementation and evaluation of the proposed approach. In [36], a data mining approach for range prediction of electric vehicle is proposed. It uses a regression model based on past driver behavior (separated in vehicle-related, driver-related and environment-related parameters) to estimate the available range. The methodology is implemented in an Electric Vehicle Assistant as a mobile application which displays the driver centric available range on a map with a 25% uncertainty band. Although the architecture and its implementation are well explained in [36] and in consecutive publications of the same authors in [37], [38], none of these publications presents any measured result, model fit or model accuracy. This methodology contains two other drawbacks: the range is the result of the SoC requirements per unit distance, losing information on the energy consumption itself, and is not calculated on each individual segment. As a consequence, energy-efficient routes cannot be generated. Another driver centric estimation of the vehicle range is presented in [39]. A destination attainability map is calculated based on a weighed probability of choosing a route to a set of destinations. The energy consumption is calculated from speed profiles by a simplified vehicle model. The speed profiles are calculated based on a car-following algorithm which incorporates road attributes as rules. This model is evaluated by comparing the calculated maps with the model based results from the actual driven routes. A variant of that model is presented in [40], where the energy calculation is now considered a normal distributed parameter and the results are validated with the Nissan Leaf.

The literature shows there are a number of solutions already presented for energy-efficient routing of electric vehicles. The approaches vary from statistical and data-driven, to deterministic. Some of these solutions have interesting methodologies that show promising results. However, most of the presented literature has a very basic energy estimation algorithm, which lacks to include one or more influencing factors (such as altitude difference, auxiliaries, or wind) and are not based on actual measured consumption of proposed routes.

III. THE PROPOSED METHOD FOR RANGE ESTIMATION AND ENERGY-EFFICIENT ROUTING

A. Energy Consumption Prediction Model

The energy consumption prediction model is a data-driven model that combines vehicle monitoring data with road information, weather information (temperature, precipitation) and temporal data (time of the day, day of the week) to predict the energy consumptions of an electric vehicle over actual

road segments. The model has a first stage for speed profile prediction using a neural network and a second stage for energy consumption estimation, given the predicted speed profile from the first stage and other influential parameters, using a multiple linear regression model. Figure 1 presents a schematic diagram of the energy model, its inputs and outputs. The AF (aerodynamic factor) and CMF (constant motion factor) are two characteristics that were defined in [9] and are measures for the aerodynamic and inertial losses respectively. The neural network for speed profile prediction is trained from road, traffic and weather related parameters. The road segment characteristics consist of its length, the altitude difference, the road type, presence of traffic lights and information on the crossings. The crossings were categorized in straight, light right turn, heavy right turn, light left turn, and heavy left turn. The linear regression model estimates the energy consumption from the AF and CMF (predicted by the neural network), the altitude difference, the covered distance and temperature scaled time dependent variable (Aux_t, Aux_T) that represent the contribution of the auxiliaries to the energy consumption. Equation 1 expresses the energy consumption in function of its dependent variables for the energy estimation by the multiple linear regression.

$$\Delta E = B_1 \Delta s + B_2 \sum_{i=2}^n v_i^2 \Delta s_i + B_3 CMF^+ \Delta s + B_4 CMF^- \Delta s + B_5 \Delta H_{pos} + B_6 \Delta H_{neg} + B_7 Aux_T + B_8 Aux_t + \epsilon \quad (1)$$

where:

Aux	% of time the auxiliaries are switched on
B_k	Regression coefficients of term k
ΔE	Energy consumption to cover distance Δs
ΔH_{pos}	Positive elevation changes
ΔH_{neg}	Negative elevation changes
i	Measurement point i
Δs_i	Distance between measurement point $i - 1$ and i
$\Delta s = \sum_{i=2}^n \Delta s_i$	Distance driven
Δt	Time difference (duration)
T	Ambient temperature in $^{\circ}C$
v_i	Vehicle speed at measurement point i
CMF^-	Negative kinetic energy changes
CMF^+	Positive kinetic energy changes
ϵ	Error term

This is the cost function for the proposed model and must thus be calculated for each segment in the road network. For an elaborate description of the energy consumption model, the reader is referred to [9], which focuses on the development and evaluation of this energy prediction model.

B. Battery Model

The range of the vehicle will essentially be a function of energy that can be drawn from the battery, and the energy consumption per unit distance. The useful energy that can be drawn from the battery depends on the remaining battery

Fig. 1. Schematic representation of the energy consumption prediction from segment road characteristics and state variables which represents the cost function.

capacity during operation, or state-of-charge (SoC), and the internal losses in the battery during operation. The internal losses in the battery are caused by battery cell balancing and current losses dissipated in the internal resistance of the battery.

Most of the existing literature studies the behavior of batteries at cell level for different types of chemistries. The internal resistance fluctuates with battery temperature and increases in time due to ageing effects [41]. The ageing of the battery is generally expressed as the state-of-health (SoH). Battery models for SoC estimation, SoH estimation and thermal behavior of Li-ion batteries exist with various levels of complexity. SoC and SoH estimation methods can be found in [42] and [43], and complex models for internal resistance calculation for the purpose of online SoC and SoH estimation on cell level are available in literature [44]. This type of dedicated modeling for complex behavior of the battery cells is out of scope for this application. However, for this application, modeling the internal resistance of the battery on pack level, together with the assumption that the SoC and SoH are known, is sufficient to translate the energy consumption into driving range.

If the battery temperature is measured, having a model that estimates the internal resistance based on the battery temperature will allow translating energy consumption into driving range. If we characterize the internal resistance by using the most simple representation of a battery, i.e. a voltage source and a resistance, the open circuit voltage (OCV) equals the terminal voltage (TV) plus the voltage drop over the internal resistance, or $OCV = R_i \cdot I_{bat} + TV$. By modeling the battery in this way, only the steady state behavior of the battery is included and transients are neglected.

C. Routing Algorithm

Calculating energy-efficient routes for EVs with SPA has 2 specific characteristics:

- The edge cost is the energy consumption
- Negative edge costs are possible

The possibility of negative edge costs impose using Bellman-Ford for single query shortest paths, if necessary with

calculation time improving heuristics, and using the currently known computational optimal Johnsons algorithm (for sparse graphs) for all-pair shortest paths. In the design of systems for querying shortest paths, the combination of network size, processing power, storage capacity, and user requirement will determine the approach. The calculation of the cost (energy consumption), can either be done during expansion (while determining the shortest path), or can be pre-calculated for the complete network if the energy cost is static and independent from the path. Pre-calculation of the energy consumption in the complete network reduces the waiting time for the user but requires pre-calculation of the look-up tables for every combination of the state variables.

Applying SPAs to a network using the energy consumption prediction model presented in Section III-A as a cost function requires some additional changes. The particularity of including turn information for the energy prediction, is the fact that the energy consumption on a segment will depend on the turn type from the preceding segment into the current segment. Moreover, some other segment characteristics of a preceding segment influence the consumption of the current one. For example, the difference in speed limit between two sequential segments will cause the driver to accelerate or decelerate accordingly. Therefore, the road type, indicated travel speed of the preceding segment and turn type into the current segment were taken into the neural network input variables. As a consequence, this cost calculation method cannot be used if the road network is represented by the classical directed graph where road segments are represented by edges and intersection by vertices. To be able to use the proposed method for energy consumption prediction, the graph representation of the road network has to be adapted in a similar way to what is done to include turn costs in literature [19], [45], [46]. Two methods can be applied: network expansion and network transformation. Figure 2 illustrates both methods on two simple network examples. The expansion method consists of replacing each vertex, representing a single intersection, with a combination of vertices and edges, according to the possible turn combinations. In example A, vertex V_3 can be travelled coming from vertex V_1 or V_2 , and the cost associated with $e_3 = (V_3, V_4)$ will vary according to the V_3 's incoming edges. To represent this choice in the graph, three extra edges and three extra vertices are added. Note that this representation guarantees that the SPA algorithm will still find the optimal solution. In example B, V_3 can be travelled coming from either e_1 or e_2 and be left on either e_3 or e_4 . To represent these combinations, vertex V_3 is replaced with 8 extra vertices and 8 edges. It is clear that with increasing complexity of the network, the adapted network expands rapidly. The second method is less straightforward, yet very elegant, and consists in transforming the graph in such way that the edges in the original graph become the vertices in the transformed graph, and the combinations of travel possibilities become edges in the transformed graph. For example A, edges e_1 , e_2 , and e_3 become nodes in the transformed graph, and the combinations of travelling V_3 from $e_1 \rightarrow e_3$ or $e_2 \rightarrow e_3$, which become the edges in the transformed graph. A similar reasoning can be done for example B. In the general

Fig. 2. Illustration of the expansion method and transformation method for the representation of a variable cost according to the turn type with two simple network examples.

case, the edges of $G = (V, E)$ become vertices of $G' = (E, E')$, $E' = ((u, v), (v, w)) \in ExE$. As for the expansion method, the transformation method will increase the number of vertices and edges, but less than with the expansion method. If v is a node in $G = (V, E)$, with n incoming edges and m outgoing edges, the node expands to $3nm - (n + m)$ edges and $(2nm)$ nodes in the expansion method, while it increases the number of vertices to $n + m$ and the number of edges to nm in the transformation method. Considering the Bellman-Ford shortest path has complexity $O(VE)$, the calculation times of the transformed graph (edge-based graph) will be smaller compared to the expanded graph. Because of the lower calculation times of the edge-based graph transformation solution, this method was implemented.

In order to make the transformed edge-based graph equivalent to its original node-based graph, the edge-based graph must be further extended with entry and exit nodes. The entry and exit nodes allow shortest paths between vertices of the node-based graph to be queried in the same way as in its edge-based form. As shortest paths are queried between vertices of a graph, queries in the edge-based graph as presented until now, would calculate the cost between two edges in the original graph. However, in order to query shortest paths in both G and G' which are equivalent (in between nodes of G), G' must be further extended such that each vertex v' of G' , corresponding to edge $e = (u, v)$ of G , can be accessed by its origin node u in G and exited by its destination node v in G . This can be done by extending the graph G' with entry vertices $V_{en} = u E_{en} = (V_{en}, e)$, with $u \in V$ of $G(V, E)$ and $e \in E$ of $G'(E, E')$, and $V_{ex} = v E_{ex} = (e, V_{ex})$, with $v \in V$ of $G(V, E)$ and $e \in E$ of $G'(E, E')$. Note that if G had n nodes, this operation will increase the number

Fig. 3. Conversion of a simple node-based network to its edge-based equivalent with the addition of entry and exit nodes.

of edges and number of edges of G' with at most $2n$. Lets consider the cost allocation of all edges, entry edges and exit edges in our specific case. In general we can say that if we consider an edge e_i with preceding edge e_{i-1} , the edge cost of e_i will be a function of the characteristics of the preceding edge (characteristics of the edge and turn type from $i \rightarrow i - 1$). Therefore, we define the cost associated with an edge of the edge-based graph $c(e_{i-1}, e_i)$ as the energy consumption at reaching the end of segment i , considering we travelled from edge $i - 1$. To define the cost associated with the entry and exit edge, consider the simple example presented in Figure 3 and apply this to the general case. If we start in node i of the node-based graph, we will enter the edge-based graph through the entry node en which has an associated of $c = f(en, e_i)$, according to this definition. Since en does not represent an actual road segment, its characteristics and the turn type associated with travelling from en to e_i , do not exist and cannot be allocated. The cost allocated to entry edges are therefore calculated based on an average consumption value. For the exit edge, the case is simpler. By calculating all cost according to the procedure above, the cost when residing in a vertex of G' , which represents a road segment (=edge in the node-based graph), is the energy consumption after the segment is travelled. Exiting from the last vertex through the exit edge to the exit vertex (=destination node in the node-based graph), should therefore have a cost that equals zero. Figure 3 illustrates the transformation from a node-based graph to an edge based graph, with entry- and exit node extension, and the cost allocation according to the reasoning above.

D. Integrated Model for Range Estimation and Energy-Efficient Routing

The objective of this research is a model for energy consumption prediction and range estimation, capable of energy efficient-routing. If we use the energy prediction model

Integrated model for energy-efficient routing and range-estimation

Fig. 4. Overview of the complete integrated model for energy-efficient routing and range estimation.

presented in III-A to calculate and predict the energy consumption on all road segments in network, and apply the SPA on the transformed edge-based representation of the road network, energy optimal routes are generated. If we input the energy consumption over the calculated path into the temperature dependent battery capacity model, such as presented in Section III-B, together with information on the SoC and SoH, the model can predict the remaining driving range at the destination in the form of the remaining SoC. The lay-out of this integrated model for energy consumption prediction, energy-efficient routing and range estimation is presented in Figure 4.

IV. IMPLEMENTATION

This integrated model is implemented in an offline way to investigate the impact of energy-efficient optimal solutions on the route choice. The model is implemented for the a selection of the network Brussels Capital Region (BCR) network for a Nissan Leaf 2013 model. The model is implemented on a selection of the road network to limit the calculation time of the energy prediction on all segments in the selected road network. Since the energy consumption has to be re-calculated on the complete network with changing state variable, limiting the implemented network improves the workability for this study. The network pre-processing (e.g. calculating crossing category, calculating altitude differences) on segments is done in ArcGIS®. Apart from the network pre-processing, the complete integrated model was implemented in Matlab®. The network is imported in the form of a shapefile, which Matlab allows to visualize. The network described in the shapefile is then translated into its mathematical representation of a directed graph after performing the following actions:

- duplicating the edges corresponding to two-way streets (while inverting the road attributes of heading and altitude difference)

- inverting edges corresponding to one-way streets with opposing traffic flow and edge directions
- deleting edges which correspond to road segments with unknown road type or closed for passenger transportation (e.g. roads in parks).
- create the node-based graph associated with the selected road network must then be transformed into an edge-based graph, as explained in Section III.

The energy-optimal solutions will be calculated on the edge-based graph using Bellman-Ford algorithm, while distance-optimal solutions are calculated using Dijkstra algorithm on the original node-based graph (which is the benchmark of current practice in classical routing). The network size, the size of its node-based graph representation, and the size of its edge-based representation is given in Table I. The table also presents values for the calculation times to build the node-based graph, the edge-based graph and the average calculation time for the time-optimal and distance-optimal solutions of 5 randomly chosen origin and destinations with a 2.9GHz Intel®Xeon®CPU E3-1545M v5 processor. Table I shows the size of the edge-based graph is significantly higher with approximately 5 times the number of vertices and edges of the node-based graph. The calculation time for the energy-optimal routes with Bellman-Ford on the edge-based graph is an order of magnitude slower than running Dijkstra on the node-based graph for distance-optimal routes. Calculating the energy cost for the selected network for one combination of state variables was time-consuming and must therefore be executed and stored prior to querying origin destination pairs in order to be useable in real user applications.

To construct the temperature dependent battery internal resistance model, battery temperature data of different vehicles was used since battery temperature data was lacking for the vehicles that provided the data to build the energy consumption model. Although this might impact the accuracy of the range

TABLE I

OVERVIEW OF THE NETWORK SIZE, THE SIZE OF ITS REPRESENTATION BY NODE-BASED GRAPH, AND THE SIZE OF ITS EQUIVALENT EDGE-BASED GRAPH. THE AVERAGE CALCULATION TIME OF RUNNING DIJKSTRA ON THE NODE-BASED GRAPH AND BELLMAN-FORD ON THE EDGE-BASED GRAPH ON 5 ORIGIN-DESTINATION PAIRS

Road Network	Node-based Graph				Edge-based Graph			
# Segments	# E	# V	Build Time (s)	Dijkstra (s)	# E	# V	Build Time(s)	Bellman-Ford (s)
37822	52057	24815	12.5	0.0052	252446	101639	108.9 (+12.5)	0.014

Fig. 5. Regression plot for the battery internal resistance in the 4-9°C and 50-55% SoC bins.

Fig. 6. Internal resistance for all temperature regions and SoC bins for one vehicle in the dataset.

prediction of the model in its current state, it demonstrates the methodology. These vehicles were equipped with a 27kWh Li-Ion (LiFePO_4) battery pack, where both battery temperature and terminal voltage were monitored. The terminal voltage of the battery and the battery current can be used to calculate the internal resistance using the linear equation above from Section III-B. Because the open circuit voltage of the battery changes with its remaining SoC, the measurements are grouped into SoC bins of 5% SoC and temperature bins of 5 °C. The internal resistance is then calculated by applying linear regression to the data points. The internal resistance will be the additive inverse of the slope of the regression line. As an example, Figure 5 illustrates the result of the linear regression to determine the battery's internal resistance for the 4-9 °C, 50-55% SoC bins for one vehicle of the dataset. A similar linear regression is used to determine the internal resistance in all temperature regions and SoC bins, which are presented in Figure 6. The internal resistance shows a clear temperature dependence and a slight linear increase with decreasing SoC. Although Figure 6 shows a clear temperature dependence of the battery's internal resistance, the associated losses will also depend on the load profile (current). The battery losses, $P_{\text{Loss}_{\text{battery}}}$, dissipated in the internal resistance R_{internal} by drawing a current I_{battery} equal $P_{\text{Loss}_{\text{battery}}} = R_{\text{internal}} I_{\text{battery}}^2$.

Figure 7 presents the average resistive losses relative to the total power consumption in function of the battery temperature during braking and driving for the same vehicle of the dataset. It shows that the resistive losses during braking are about 1%,

Fig. 7. Average resistive battery losses in function of the battery temperature during braking and driving for 1 vehicle of the dataset.

while the resistive losses during driving are between 3-6%, depending on the battery temperature. The limited current during regeneration leads to these lower battery losses for braking compared to driving.

V. RESULTS

A. E-Routing Analysis

To evaluate the performance and application potential of the proposed model for energy efficient routing, the model will be applied to a chosen scenario and to a random selection of origin-destination pairs. The first allows to have feel with the dynamics (different energy consumption influencing factors) that shift a time-optimal or distance-optimal route to an energy-optimal route, while the latter allows to have a more general evaluation of the effect of energy-efficient routing on

TABLE II
DESCRIPTION OF THE STATE VARIABLES OF CASE A AND CASE B OF THE GENERAL SCENARIO

Case	Origin	Destination	Temperature	Auxiliaries	Time Of Day (h)	Day of Week	Precipitation
A	E40 East	Home West	17	Off	11	Wed	None
B	E40 East	Home West	0	On	11	Wed	None

travel time and consumed energy. The following scenario is considered:

- Travelling across town: the driver approaches one side of the city on a highway and has its destination on the other side of the city.

The scenario presents a dilemma to the driver: drive through the city or go around the city using the ring way. This scenario is chosen because it is expected to occur in real-life and have non-marginal differences in travelled distance, travel time, and energy consumption. The distance-optimal, time-optimal and energy-optimal solution will be calculated with the integrated model and analyzed for different cases of the main scenario. All different set-ups of the scenario will be based on the model which was developed. All cases are based on the main scenario where a driver approaches the east side of town on a highway, and is bound for home on the outskirts of the west side of the city. The origin segment will be the last segment of the highway approaching the city before crossing the ring way R0. The first 2 cases of the scenario have the same origin and destination, but have different values of the state variables. The first case (case A) has moderate ambient temperatures without using auxiliaries and the second case has low ambient temperatures with the vehicles auxiliaries on. All other state variables are kept constant. The description of both cases and their state variables is given in Table II. To understand the general trends in the route choice, it is important to understand how distance, speed and time contribute to the energy consumption (weights in equation 1). In [9], a figure depicting the average consumption in function of trip speed illustrates the more or less constant contribution of the rolling resistance in function of speed, the decreasing contribution of accelerations with increasing speed, the increasing contribution of aerodynamic losses with increasing speed and an increasing contribution of auxiliary consumption with decreasing speed. The distance-optimal, energy-optimal, and time-optimal route for the first case as calculated by the model are presented in Figure 8a. Both the distance-optimal and energy-optimal route cross the inner city, while the time optimal route takes the ring way. This is not unexpected as the increase in distance is outweighed by the difference in travel speed along a highway route. However, the increase in aerodynamic losses during highway driving and increased distance makes the energy cost of this route much higher. Like the distance-optimal, the energy-optimal route also crosses the inner city, yet still differs for a large part of the route.

The same scenario in low ambient temperature conditions with the vehicles auxiliaries on can shift the time-distance-energy balance because of the increased impact of the travel

Fig. 8. Case A (a) & Case B (b) Bs distance-optimal route (black), energy-optimal route (green), and time-optimal route (yellow).

time on the total consumption by the auxiliaries. The distance-optimal, energy-optimal, and time-optimal route for the second case (case B) as calculated by the model are presented in Figure 8b. The energy-optimal route shifts and almost coincides with the time-optimal route. In the third (C) and fourth variant (D) of the general scenario, the origin is shifted to another highway coming into the south-east side of Brussels. Case C and D are identical to A and B respectively, except for their starting point, which shifts the distance ratio of cutting across the city and going around it. One case will have moderate ambient temperature without the use of auxiliaries, the other case low ambient temperatures with the vehicles auxiliaries on, similar to Case A and B respectively. The description of both cases and their state variables is given in Table III. The distance-optimal, energy-optimal, and time-optimal route for the third case (case C), as calculated by the model, are presented in Figure 9a. Similar to case A, the time-optimal route takes the ring way, while the, partly coinciding, distance-optimal and energy-optimal routes cross the city. In case D, with low temperatures and the vehicles auxiliaries on, only minor shifts in the energy-optimal route occur, increasing the percentage coinciding with the distance-optimal route, as is shown in Figure 9b. This means the impact of the increased distance and aerodynamic losses on total energy consumption by taking the ringway outweigh the reduction in auxiliary consumption associated with the gain in travel time for this case. In general we can state that the energy optimal route is a trade-off between travel time (speed) and distance and will lean towards the distance-optimal route in the case of a low auxiliary consumption and will lean towards the time-optimal route in the case of a high

TABLE III
DESCRIPTION OF THE STATE VARIABLES OF CASE C AND CASE D OF THE GENERAL SCENARIO

Case	Origin	Destination	Temperature	Auxiliaries	Time Of Day (h)	Day of Week	Precipitation
C	E411 East	Home West	17	Off	1	Wed	None
D	E411 East	Home West	0	On	11	Wed	None

TABLE IV
OVERVIEW OF THE RESULTS OF THE DISTANCE-, ENERGY-, AND TIME-OPTIMAL ROUTES FOR ALL FOUR CASES OF THE MAIN SCENARIO

Case	Optimal	Distance (km)	Relative to Time- Optimal	Energy (kWh)	Relative to Time- Optimal	time(s)	Relative to Time- Optimal
A	Distance	18.1	20%	3.02	-9%	0.32	45%
	Energy	18.7	-18%	2.80	-16%	0.37	68%
	Time	22.7	0%	3.33	0%	0.22	0%
B	Distance	18.1	-20%	4.22	3%	0.32	45%
	Energy	22.5	-1%	4.05	-1%	0.24	9%
	Time	22.7	0%	4.09	0%	0.22	0%
C	Distance	18.9	-38%	2.96	-31%	0.34	17%
	Energy	19.9	-34%	2.71	-37%	0.38	34%
	Time	30.3	0%	4.31	0%	0.29	0%
D	Distance	18.9	-38%	4.24	-20%	0.34	17%
	Energy	19.4	-36%	4.16	-21%	0.34	17%
	Time	30.3	0%	5.28	0%	0.29	0%

Fig. 9. Case C (a) & Case D (b) Ds distance-optimal route (black), energy-optimal route (green), and time-optimal route (yellow).

auxiliary consumption. The differences between the distance-optimal route and energy-optimal route passing through the city are small, yet generally we observe that the energy-optimal route selects roads of higher importance, with less intersections, and limits the number of turns.

The results of the distance-, energy-, and time-optimal routes for all four cases are presented in Table IV. The results are absolute values of the travelled distance, travel time, and energy consumption and show the relative difference compared to the time-optimal. The time-optimal route is selected as the reference case because it is considered the preferred choice of

a driver in general. The relative numbers presented in Table IV, indicate the gain or loss in travel time, travel distance and energy consumption in case the driver opts to divert from the time-optimal route. These numbers show the potential benefits of the different routes and could be used to inform the driver when such dilemmas present themselves. In case A, there is a moderate gain efficiency (-9%), yet a large increase in travel time (45%) for the distance-optimal route, and slightly more so for the energy-optimal route (-16% and 68% respectively). Therefore, the energy-efficient route in this case will not likely benefit the driver, unless the vehicle is critical on SoC. In case B, the obvious choice is to divert from the distance-optimal route to either the energy-efficient or time-efficient route. Since the gain in energy efficiency is insignificant (-1%) compared to a 9% loss in time between the energy-optimal and time-optimal route, the latter seems the most beneficial in this case. Note that the increase in energy consumption between the energy-optimal routes of case A and case B is 45%, illustrating the large choice-based gain or loss in different conditions. Case C is identical to case A except for its starting point, which makes cutting across the city much shorter than going around it. Therefore, the energy-efficient route becomes much more attractive to drivers, because of its large energy-efficiency gain (-37%) and moderate time-loss (34%). Furthermore, the distance-optimal route might be even more attractive because its energy-efficiency gain (-31%) is almost as large as the energy-optimal route, but its time loss is

TABLE V

OVERVIEW OF THE AVERAGE RELATIVE DIFFERENCES IN DISTANCE, TRAVEL TIME, AND CONSUMED ENERGY BETWEEN THE ENERGY-OPTIMAL ROUTES COMPARED TO THE TIME-OPTIMAL ROUTES FOR A RANDOM SELECTION OF 100 ORIGIN-DESTINATION PAIRS

Low ambient temperatures			Moderate ambient temperatures		
Relative difference Distance (%)	Relative difference Time (%)	Relative difference Energy (%)	Relative difference Distance (%)	Relative difference Time (%)	Relative difference Energy (%)
-6.3	10.8	-8.3	-8.6	22.5	-16.6

only half (17%). Case D has similar time losses as Case C, yet loses competitiveness with the time-optimal route because of its decreased energy-efficiency gain. These scenarios and their different cases illustrate energy-optimal routes shift according to the ratio of travel time and travel distance, and according to values of the state-variables. Of course, road altitude differences, intersections, road types, which are also accounted for in the energy consumption prediction model, will also further shift the energy-optimal route and differentiate it from the time-optimal route or distance-optimal route it is leaning towards. Depending on the relative gain or loss of travel time and energy consumption, drivers can make informed decisions on the appropriate route.

For a more general evaluation of the e-routes, the model was applied to a random selection of 100 origin-destination pairs in the case with moderate ambient temperature and the case with low ambient temperature conditions (and use of heating), similarly to what was done before with the difference between case A and B, and case C and D. The average relative differences in travel distance, travel time, and consumed energy between the time-optimal route and energy-optimal route for both conditions are given in Table V. To illustrate the spread in the relative differences, a boxplot is given in Figure 10. The results are consistent to what was observed in the analysis of the scenario. In both temperature conditions, the numbers show an average reduction of the energy consumption at a considerable time loss for the energy-optimal routes compared to the time-optimal routes. In the case with low ambient temperatures (and use of auxiliaries), the energy savings and time losses of the e-routes are smaller compared to the case with moderate temperatures. This is consistent with the case B of the examined scenario, where it was observed that in the case of an important consumption of the auxiliaries, the travel time has an important contribution to the energy consumption, which shifts the e-route closer to the time-optimal case. The 16.6% average energy consumption reduction for the case with moderate ambient temperatures demonstrate that, on average, important energy savings can be obtained by consistently applying e-routing, while the boxplot illustrate there is large spread in the potential energy consumption reductions which will probably lead to a case by case evaluation by the driver for a route choice depending on his priorities.

B. Real-Life Tests

To test and evaluate the operation of the integrated model in real-life, case A of the general scenario and its inverse (inverting origin and destination) was driven with an electric vehicle. The electric vehicle at hand is a 2011

Fig. 10. Boxplot for the relative difference in energy consumption for the random selection of 100 origin-destination pairs in both low and moderate ambient temperature conditions.

Nissan Leaf which has been used by a MOBI research group staff member for the last year. The vehicle was purchased in 2013 and had at the time of test a mileage over 83.000 km. The energy estimation model is developed based on the last 6 months of data from the vehicle, according to the methodology presented in III-A. The regression coefficient for negative altitude differences (B_4 in equation 1) was larger than the regression coefficient for positive altitude differences (B_3 in equation 1). Because this is not only physically impossible, but can also lead to the perverse effect that altitude differences are preferred instead of being avoided for energy-efficient routes, and lead to negative cycles in the graph representing the road network, this regression model is not workable in the integrated model. Figure 11 illustrates this situation on a very simple network represented by a graph with three vertices with associated altitude, and three edges. Travelling from node $V_1 \rightarrow V_2 \rightarrow V_3 \rightarrow V_1$, with associated altitudes 1, 3, 5 and 1 respectively, will cause the cycle to have a negative cost (e.g. $2 + 2 - 6 = -2$) if the regression coefficient for negative altitude differences is larger than the regression coefficient for positive altitude changes (e.g. at ratio 1.5), and will cause any shortest path to evolve to minus infinity. To deal with this issue, the model was changed to have only one term for the altitude difference contribution. The formula then becomes (cf. Section III-A):

$$\Delta E = B_1 \Delta s + B_2 \sum_{i=2}^n v_i^2 \Delta s_i + B_3 \sum_{i=2}^n |v_i^2 - v_{i-1}^2| + B_4 \Delta H + B_5 |20 - T| t Aux + B_6 \Delta t + \epsilon \quad (2)$$

Note that this will effectively shift the contribution of the intermediate altitude differences to the other terms and only

TABLE VI
RESULT OF THE MULTIPLE LINEAR REGRESSION FOR THE 2011 NISSAN LEAF TEST VEHICLE

2011 Nissan Leaf Test Vehicle								
$R^2 =$ 0.89	Intercept	Rolling Resistance B_1	Aerodynamic B_2	Positive Acceleration (B_3)	Negative Acceleration (B_4)	Altitude Difference (B_5)	Duration (B_6)	Auxiliaries (B_7)
Bi	8.08105	0.0748	3.78106	1.79105	1.29105	0.00221	0.182	0.059
sEi	0.000775	0.00165	0.0551	$3.8710 - 07$	$3.5310 - 07$	0.00880	$1.3410 - 07$	$7.3410 - 05$
p-values	<1	<0.0001	<0.0001	<0.0001	< 0.0001	<0.0001	< 0.001	< 0.0001

Fig. 11. Example of the creation of negative cycles because of the larger energy recovery during downhill than energy consumption during uphill, illustrated with a simple 3-segment network.

account for the net altitude differences explicitly. This also means that intermediate altitude differences will no longer affect route choice. However, the impact on the prediction accuracy and route choice is expected to be limited because of the small contribution of intermediate altitude differences in the BCR region to the total consumption. The regression coefficients as used by the model are presented in Table VI. The distance-optimal, energy-optimal, and time-optimal route for the real-life test case as calculated by the integrated model are presented in Figure 12. The results of the model predictions and measurement of the routes are presented in Table VII. The predicted and measured values of the energy consumption match well and the ranking of the routes in terms of their travel distance, energy consumption and travel time, is preserved, thus satisfying the prime goals of the integrated model for energy-efficient routing. If we consider the time-optimal route as the benchmark route, the relative differences of the distance-optimal and energy-optimal routes are presented in Table VIII. The table shows that the measured travel times are way off the model predictions, due to the use of the available link travel times which do not take into account a time cost for passing intersections. Table VIII also shows the trip distances in the model slightly differ from the measured trip distances, which is due to the difference between the lengths of the links (segments) in the road database and the GPS measured distances during the trip, which were affected by GPS inaccuracy and long standstill times during inner city trips. However, this will not affect the result as all calculations are done based on the road database segments' length. Similar to the analysis made in Section V-A above, despite significant

Fig. 12. The real-life test cases distance-optimal route (black), energy-optimal route (green), and time-optimal route (yellow).

energy-efficiency gains (around 30%), the large increase in travel time for the energy-efficient routes compared to the time-optimal route makes these energy-efficient routes in these cases unattractive from the drivers point of view, unless the vehicle is critical on SoC. In terms of accuracy, the model prediction shows small errors for the Home-E40 case (1-7%) and reasonable errors for the E40-Home case (12%-17%). These measurements serve to proof this is a functional model for energy consumption prediction of electric vehicles and energy-efficient routing, with good accuracy.

VI. DISCUSSION

The scenario considered in the evaluation of the proposed solution is chosen such that is expected to generate non-trivial differences between a distance-optimal, time-optimal and energy-optimal route from an origin to a destination in order to illustrate to the reader the potential of energy-efficient routing and the usability of the proposed model. However, more thorough investigation of the potential of energy-efficient routing can be performed (e.g. random selection of

TABLE VII
RESULTS OF THE PREDICTED AND MEASURED ENERGY CONSUMPTION VALUES FOR THE DISTANCE, ENERGY, AND TIME-OPTIMAL ROUTES FOR THE CHOSEN SCENARIO

	Optimal	Model Predictions			Measurements			
		Distance (km)	Energy (kWh)	Time (s)	Distance (km)	Energy (kWh)	Time (h)	Relative Difference Energy (%)
E40 - Home	Distance	17.7	2.96	0.33	19.4	2.88	0.71	+3%
	Energy	19	2.73	0.39	22.1	2.71	0.81	+7%
	Time	22.7	3.83	0.22	24.0	3.88	0.35	-1%
	Optimal	Model Predictions			Measurements			
		Distance (km)	Energy (kWh)	Time (s)	Distance (km)	Energy (kWh)	Time (h)	Relative Difference Energy (%)
Home - E40	Distance	18.1	3.01	0.32	19.1	2.49	0.62	+17%
	Energy	18.9	2.79	0.35	20.0	2.34	0.85	+15%
	Time	23.2	3.83	0.22	23.1	3.36	0.31	+12%

TABLE VIII
THE RELATIVE DIFFERENCE IN TRAVEL DISTANCE, TRAVEL TIME AND CONSUMED ENERGY FOR THE DISTANCE-OPTIMAL AND ENERGY-OPTIMAL ROUTE COMPARED TO THE TIME-OPTIMAL ROUTE

	Optimal	Model Predictions			Measurements		
		Distance increase	Energy increase	Time increase	Distance increase	Energy increase	Time increase
E40 - Home	Distance	-22%	-23%	+50%	+19%	-25%	+102%
	Energy	-16%	-29%	+77%	+8%	-30%	+131%
	Time	0%	0%	0%	0%	0%	0%
	Optimal	Model Predictions			Measurements		
Home - E40	Distance	-22%	-21 %	+45%	+17%	-26%	+100%
	Energy	-19%	-27%	+59%	+13%	-30%	+170%
	Time	0%	0%	0%	0%	0%	0%

origin-destination pairs, or cases with different traffic conditions) using the proposed solution, but this lies outside of the scope of this paper, which focuses development of the model itself. The validation of the model has been done on times where traffic conditions were considered congestion free, as no real-time information on the traffic conditions was available and the lack of real-time traffic conditions was already highlighted as a cause for reduced accuracy of the energy consumption prediction in the thorough evaluation that of part of this model in [9].

VII. CONCLUSIONS

This paper proposes an integrated model for range estimation and energy-efficient routing. It is based on the energy consumption prediction model, presented in [9], and extended

with a temperature dependent, internal resistance model of the EV battery, in order to translate energy consumption into driving range. The energy consumption is predicted on all segments of a road network, and shortest path algorithms are applied to generate energy-efficient routes. The road network is represented by a digraph with edges and vertices, where the edges represent road segment and vertices represent intersections. Because the proposed model calculates the energy consumption of a segment based on its characteristics and the characteristic of the preceding road segment, classical shortest path algorithms cannot be applied to the graph in its standard form. The graph is transformed into an edge-based graph where vertices now represent segments and edges represent combinations of segments. Transforming the network in this way increases the number of nodes and edges in

the graph, which will increase calculation time of the SPA by an order of magnitude for the selected network. To be able to deal with negative edge costs (which corresponds to energy recovery), Bellman-Fords SPA is applied. The integrated model is investigated in a selection of the road network by means of evaluating a scenario with multiple cases, and using a random selection of 100 origin-destination pairs. The results showed energy-efficient routes with efficiency gains up to 37% for specific cases of the chosen scenario and 8-16% on average for a random selection of origin-destination pairs. Further analysis showed that the energy-optimal route is different from the time- and distance-optimal route, but leans towards a distance optimal in the case of low auxiliary consumption and leans towards a time-optimal in the case of high auxiliary consumption. When the energy-optimal is close to the distance-optimal, it tends to avoid intersections and turns, and tends to select roads of higher importance compared to the distance-optimal. Analysis also showed that the gain in energy-efficiency often comes at the cost of high increase of travel time (up to 68% for the scenario and 11-23% on average for the random selection). These results indicate consistently applying e-routing can lead to important energy savings, yet is likely to be subject to a case by case evaluation by the driver for his preferred route based on his priorities (such as the vehicle being critical on SoC or time pressure). Presenting the driver with different options will allow him to make an informed decision regarding his preferred route. The integrated model for energy-efficient routing was also tested in real-life for one case of the chosen scenario. The measured results showed a good match with the predicted values for the energy consumption (a 9% mean relative error) and preserved the ranking of the routes in terms of the travelled distance, travel time and energy consumption of all routes. The proposed integrated model is thus a functional model for energy consumption in real-life, that differentiates many energy consumption influencing factors, and is capable of producing energy-efficient routes.

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