Smart Driving and Charging Can Help Reconciliate Limited Battery Size and Long-Distance Trips for Electric Vehicles Without Compromising on Trip Time

Giovanni de Nunzio, Volker Döge, Ian Faye, Vittorio Ravello, Antonio Sciarretta, Patrizio Turco

Transport Research Arena (TRA) Conference

Smart Driving and Charging Can Help Reconciliate Limited Battery Size and Long-Distance Trips for Electric Vehicles Without Compromising on Trip Time

Giovanni De Nunzio[b]*, Volker Döge[a], Ian Faye[a], Vittorio Ravello[c], Antonio Sciarretta[b], Patrizio Turco[c]

[a] *Robert Bosch GmbH, Postfach 300240, Stuttgart 70442, Germany*
[b] *IFP Energies nouvelles, 1 et 4 avenue de Bois-Préau, 92852 Rueil-Malmaison, France*
[c] *Automotive Research and Advanced Engineering, Centro Ricerche Fiat, 10043 Orbassano, Italy*

Abstract

Rethinking electric mobility in terms of user needs, vehicle characteristics and affordability, as well as actual driving conditions is the motivation for this paper. Studies and experience have highlighted that users' range anxiety may be alleviated by intelligent technological solutions. In this work, a comprehensive investigation of several such solutions and their impact on overall trip time for long-distance journeys has been carried out. In particular, the impact of battery size, driving speed, energy consumption, as well as charging strategy (i.e. sequence of events and charging power) has been evaluated. The goal is to understand how to best influence driving operation (in terms of driving speed and charging strategy) for given physical design parameters (battery size, maximum charging power, etc.) and make long-distance trips feasible even with smaller battery capacities.

Keywords: electric vehicles; range anxiety; eco-routing; eco-driving; smart charging; long-distance trips

Introduction

Rethinking electric mobility in terms of real user needs, vehicle characteristics and affordability, as well as actual driving conditions is the motivation for this paper from the CEVOLVER project. Studies and experience have highlighted that users' range anxiety may be alleviated by intelligent technological

* Corresponding author. Tel.: +33 437702450
E-mail address: giovanni.de-nunzio@ifpen.fr

solutions. Schoenberg and Dressler (2019) show that since the charging infrastructure is not yet ubiquitous, appropriate route planning for electric vehicles (EVs) is necessary. Many route and charging planners exist in the literature for many different objectives. Schoenberg and Dressler (2019) and Souley et al. (2021) focus on travel time, Alizadeh et al. (2014) aim to find individual and collective optimum in terms of both time and energy cost, Wang et al. (2018) target trade-offs of several criteria including energy consumption for traction. Accurate estimation of energy consumption is critical for EVs since it has a direct impact on the charging needs and travel time, as discussed in Morlock et al. (2019) and De Nunzio et al. (2020). However, very few studies focus on other aspects or parameters influencing drivers' inclination towards EVs adoption. For instance, Luo et al. (2020) investigate battery swap opportunities to increase driving range, while Liu et al. (2021) consider optimal planning of the charging infrastructure location to reduce range anxiety.

This work builds upon the results presented in Brandes et al. (2020) and De Nunzio et al. (2020), in which a smart driving and charging solution to minimize trip time on long-distance journeys was presented. A comprehensive numerical evaluation of the proposed route and charging planning solution has been now carried out with the purpose of investigating the impact of several parameters' variation under fixed real-world conditions. In particular, the impact of battery size, driving speed, energy consumption, as well as charging strategy (i.e. sequence of events, charging power and duration) has been evaluated. The goal is to understand how to best influence driving operation (in terms of driving speed and charging strategy) for specific physical design parameters (battery size, maximum charging power, etc.). The underlying motivation for gaining this knowledge is to provide the user with a holistic solution for affordable electromobility by removing a misconception that long trips are only possible with large battery capacities. This study also provides users and car makers with a better understanding of which physical design parameters and battery sizes best match with desired driving operation. Reducing battery size will reduce the total cost of ownership of the electric vehicle, which intrinsically has a large positive impact on the energy efficiency, the environment, and the society. Vehicle buyers may be reluctant to choose such vehicles since they view them as not suitable for their occasional long trips, several times a year or less. This paper clearly shows that such trips are possible even today with much smaller battery capacities, but require intelligent technical solutions to support the driver, such as speed control, fast charging, and optimal charging strategies. The necessary adaptive cruise control systems will add only little cost to the vehicle in comparison to the alternative of oversizing batteries, while contributing to saving energy and increasing road safety. Substantial improvements over unsupported driving are highlighted in the results.

Methodology

In this work, the modeling and optimization framework presented in De Nunzio et al. (2020) is adapted for carrying out a comprehensive parameter variation analysis for the long-distance routing of EVs. A series of realistic parameters of the journey have been identified and simulated. In the following the holistic modeling approach for the road network, with currently existing fast charging infrastructure along the route, the vehicle's energy consumption and travel time including charging time, as well as the optimization objective of the routing problem are summarized.

Modeling the road network as a graph

The road network can be naturally modeled as a directed graph, where road segments are denoted as arcs and intersections are denoted as nodes. In this work, the directed graph is weighted with travel time or energy consumption costs and is used to calculate the optimal route to go from an origin to a destination by means of a shortest-path algorithm. Since long-distance route planning for EVs with charging capabilities is considered here, the routing decisions are not only made in terms of arcs choice, but additional decision variables need to be included. This is achieved by expanding the graph as a multigraph (i.e. multiple arcs connecting a same pair of nodes), by creating additional arcs where multiple decisions are possible and combining this with real-world traffic data.

Speed multigraph expansion

The first additional decision variable allows the trip planner in the simulation to adapt the driving speed on certain road segments along the route to find the right trade-off between trip time and energy expenditure. In other words, on certain high-speed portions of the route, it might be worth traveling at a lower speed than the average traffic speed in order to reduce energy consumption, and therefore reduce the amount of energy required to complete the trip, which may ultimately result in reducing the number of stops to charge the battery. In this work the road segments with an average traffic speed v_{traf} higher than a certain threshold v_{cruise} are duplicated in the speed multigraph by creating as many copies as the desired alternatives of cruise speed. This means that on those segments the optimal trip planner will be able to choose between traveling at the speed v_{traf} and traveling at the speed v_{cruise}, and generate the optimal speed profile over the entire planned journey.

Charging multigraph expansion

The second additional decision variable allows the trip planner to choose the location of the charging events along the route and the amount of energy to recover during charging. All the arcs of the graph originating from a node with a charging point are replicated in the charging multigraph by creating as many copies as the predefined levels of energy that is possible to recover during charge. The allowed levels of charge with respect to energy content are defined here as $\delta_c \in \{0, 10, 20, \dots, 100\}$%, expressed as a percentage of the battery net capacity (or usable capacity) C. Therefore, each arc originating from a node with a charging point is modeled as 11 different arcs in the charging multigraph, one arc for each possible predefined value of δ_c. Thus, whenever a charging station is available, the optimal trip planner will be able to choose between skipping charge altogether and charging by specific amounts as multiples of 10% of net capacity.

Energy consumption model

The energy consumption of the electric vehicle is obtained via a model-based approach by considering vehicle longitudinal dynamics, powertrain and auxiliary power for thermal comfort. The vehicle parameters, efficiency factors and electric drive losses data were provided by "Centro Ricerche Fiat" (CRF). The auxiliary power demand is modeled as a convex function of the ambient temperature, available on each road segment, as in De Nunzio et al. (2017). The battery is assumed to be kept in the ideal temperature range of 25-35°C by its management system, as in De Cauwer et al. (2022). An overall average electric drive efficiency is considered in this work and varied as a parameter in the simulation experiments. Now denote a generic energy consumption weight ω_e for each arc of the routing graph considering both required energy for travel and energy recovery on the arcs where charging is possible.

Travel and charging time model

The time required to traverse a road segment depends on the type of arc in the routing graph. The travel time estimate on an arc where there are no additional decisions in terms of speed and charging is simply determined based on the traffic speed and the segment length L, as L/v_{traf}. On the arcs where the driving speed may be reduced to v_{cruise}, the travel time takes on two values, that is either L/v_{traf} or L/v_{cruise}.

Furthermore, on the arcs where a charge event may occur, the travel time estimate must consider several contributions to correctly describe the time needed for charging. A term t_d is used to depict the detour time required to reach the charger location. A term t_s represents the time spent after stopping the vehicle to interact with the charger and set-up the charge. A last term t_c corresponds to the actual charging time, which depends on the battery state of charge (SoC) at the beginning of the charge, the final SoC, the battery net capacity and the charging power. In order to correctly estimate the charging time t_c, a charging model calibrated with experimental data provided by CRF was used in this work. Figure 1 shows the charging time curve for the considered battery with a net capacity of 38 kWh and accepted battery input charging power of 50 kW or 85 kW. Now define a generic trip-time weight for each arc of the routing graph as ω_t considering both required time for travel and for charging.

Routing problem definition

Finally, the route planning problem can be formulated as a bi-objective optimization aiming to find the best trade-off between trip time and energy consumption. The objective function J to be minimized over the entire trip can be easily expressed as a weighted sum of time and energy costs (ω_t and ω_e) with a trade-off weight $\lambda \in [0,1]$:

$$J = \lambda\omega_t + (1-\lambda)\omega_e \tag{1}$$

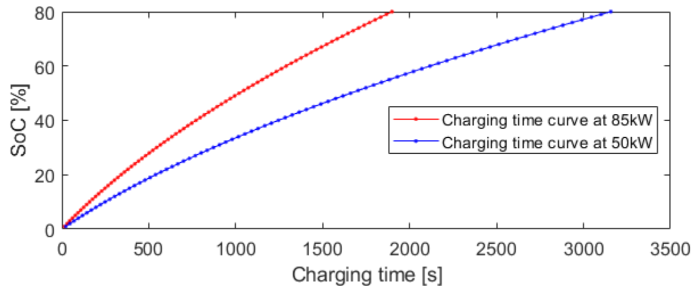


Figure 1 DC fast charging time profile for a battery with a net capacity of 38 kWh and different charging powers.

To resume, in the proposed approach some model parameters are constant for comparison consistency: traffic conditions, ambient temperature, detour time t_d and stop time t_s. Some parameters are varied to assess their impact on the results: battery net capacity, cruise speed alternative v_{cruise}, electric drive efficiency and optimization trade-off λ. The input variables optimized by the proposed trip planner, also referred to as the optimizer, are: route choice, driving speed, charging location and amount of energy transferred during charging. The analyzed output variables are: overall trip energy consumption, overall trip time, number of charging events (or stops), overall trip mean speed.

Simulation experiments

Numerous simulation experiments have been conducted to evaluate the solution variability to different parameters and different driving and charging strategies. The simulation scenario was provided by the European Union's funded project CEVOLVER and it corresponds to a long-distance trip of about 800 km from Stuttgart, Germany, to Nice, France, across the Alps. The considered electric vehicle is a Fiat 500e. The topography information was provided by HERE Maps. The location of existing charging stations is known and retrieved from OpenChargeMap and, in this analysis, they are all assumed available for charging. An illustration of the route with the existing on-route direct-current (DC) fast charging stations with a charging power between 50 kW and 150 kW is given in Figure 2.

The parameters and their numerical values that were used in the simulations are discussed hereafter:

- The battery net capacity C is increased from the nominal net capacity of the considered vehicle (i.e. 38 kWh), to a maximum hypothetical usable capacity of 68 kWh with steps of 5 kWh. This parameter variation is meant to investigate the impact of a larger battery on the driving and charging strategy, but also and more importantly on the overall trip time. It is assumed that the battery capacity variations do not have an impact on the vehicle parameters, such as its overall mass or aerodynamic properties. This was assumed in order not to bias the results in the scope of this paper with secondary effects. It can be reasonably assumed that in the upcoming future larger battery capacities can be achieved without too much impact on the vehicle mass due to technological advancements on cells gravimetric energy density.

- The alternative cruise speed parameter v_{cruise} was varied between 135 km/h and 90 km/h with steps of 5 km/h, and only one value was used for each experiment. As discussed before, on the

Figure 2 Illustration of the route between Stuttgart, Germany, and Nice, France, with all the existing charging stations identified by red markers.

road segments where the average traffic speed v_{traf} is higher than v_{cruise}, the additional cruise speed option v_{cruise} is added on the segment.

- The electric drive efficiency used as a parameter in the energy consumption model was also assumed to take on two different values. The first value of 85% efficiency corresponds to the data provided by the car maker for the considered vehicle and represents a good approximation of the current state-of-the-art in terms of EVs electric drive performance. The other considered value was 90% efficiency, which represents a fair estimate of what technological improvement will be able to achieve within the next 5 to 10 years on production vehicles.

The other parameters that were kept constant in the experiments are:

- The traffic conditions correspond to morning rush hour at 8am of a typical working day, as retrieved from HERE Maps, and were stored for repeated use in order to make the results comparable.

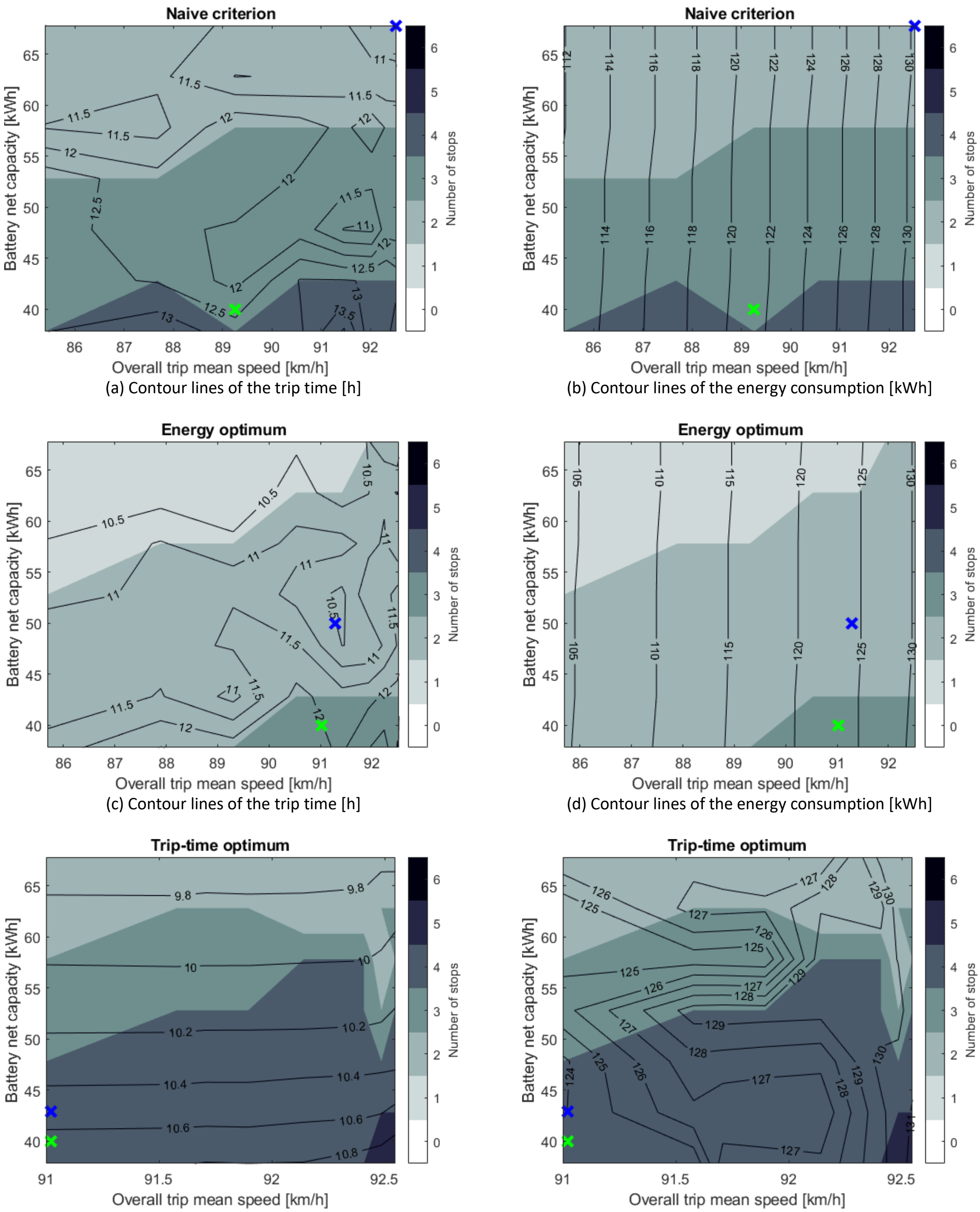
- The ambient temperature was assumed to be constant at 20 °C along the entire route. This assumption allows us to focus on the effects of smart driving and battery capacity on the overall driving experience without local and unpredictable perturbations. In practice, this translates into a constant auxiliary power demand of 650 W.

- The parameters of the travel time model were set to $t_d = 60$ seconds and $t_s = 180$ seconds.

Three different driving and charging strategies have been compared for this paper. The first strategy, named ***naive criterion***, serves as a baseline and simply aims to mimic the likely behavior of an unassisted driver who, once selected the fastest route, would start searching for the next available fast charging station as soon as the battery state of charge drops below a fixed threshold, set here at 40% SoC (i.e. about 150-200 km remaining range for the tested battery net capacities). This seems to be a realistic choice for an unassisted driver, most likely unfamiliar with the existing charging infrastructure during long trips. Note that the naïve criterion considers the cruise speed parameter v_{cruise} as a speed limit, thus simulating a more cautious driver not willing to exceed a maximum driving speed on a long trip. The second charging strategy is called ***energy optimum*** and aims to minimize only energy consumption by determining the optimal combination of input variables as defined in Section 2.4. This charging strategy corresponds to a choice of $\lambda = 0$ in Equation (1). The third strategy is called ***trip-time optimum*** and aims to minimize total trip time by determining the optimal combination of the same input variables as defined in Section 2.4. With this strategy, the suggested driving cruise speed generally matches the traffic speed and is reduced only on road sections with higher consumption in order to save time by reducing energy needs during charging. This corresponds to a choice of $\lambda = 1$.

A novel means of displaying the multi-dimensional results and dependencies among the different parameters was developed in Figure 3, with battery net capacity plotted against trip mean speed, and can be seen as electromobility maps. Note that while battery net capacity is a design parameter, trip mean speed is an output of the optimal trip planner and reflects how the optimized driving speed, depending on the cruise speed parameter, can impact the overall trip time. The number of charging stops is displayed as a background colormap and ranges from 1 to 5. The overall trip time (3a, 3c, 3e) and energy consumption (3b, 3d, 3f) results for each strategy are displayed as contour lines to easily visualize the combination of parameters yielding the same results. The respective optimization scenario results in uniform contours (either energy, 3d, or time, 3e) for that strategy, but at the cost of a complex "conjugate" (e. g. time, 3c, or energy 3d). The naïve criterion shown in Figure 3a and 3b is unsupported and will always follow the cruise speed which inherently favors energy savings and hence results in uniform energy consumption, 3b. Figure 3c and 3d show the results for the energy optimum strategy is shown in Figures 3c and 3d, and the trip-time optimum strategy in Figures 3e and 3f. Users that are willing to make more stops (in-line with driving club recommendations) and to use driver assistance systems during a long trip experience a higher potential to save on battery size and cost (up to 35% savings on the battery cost), and still carry out a long trip in reasonable time (roughly only 8% more). The unsupported driver only willing to accept 2 stops along the journey would need at least a 55-kWh battery installed in the vehicle, and even then the trip would take 10.5 hours (with a 68-kWh battery) in the best case (see blue crosses in Figure 3a and 3b). The energy consumption contour lines in Figure 3b are all vertical, showing that the alternative cruise speed parameter allows the naïve criterion to consistently reduce energy consumption as lower cruise speeds are chosen, and this independently of the battery net capacity. The results confirm the intuition that an unsupported driver would tend to invest in larger battery capacities to try to reduce travel time. Industry currently also seems to follow a similar trend. Recently Mercedes-Benz covered more than 1000 km over the Alps on a single charge with a prototype vehicle using a 100-kWh battery. The trip mean speed was 87 km/h for a trip time of 12 hours.

The first supported strategy (energy optimum), in Figure 3c and 3d, shows that the optimizer is able to find the best combination of alternative cruise speeds, charging stations and charging durations in order to improve both



(a) Contour lines of the trip time [h]
(b) Contour lines of the energy consumption [kWh]
(c) Contour lines of the trip time [h]
(d) Contour lines of the energy consumption [kWh]
(e) Contour lines of the trip time [h]
(f) Contour lines of the energy consumption [kWh]

Figure 3 Contour lines of the trip time (on the left) and energy consumption (on the right) for the three strategies, naive criterion, energy optimum and trip-time optimum (from top to bottom). The results are displayed for different battery net capacities and overall trip mean speed. The number of stops is indicated by the background colormap. Crosses indicate the location of the examples made in the text.

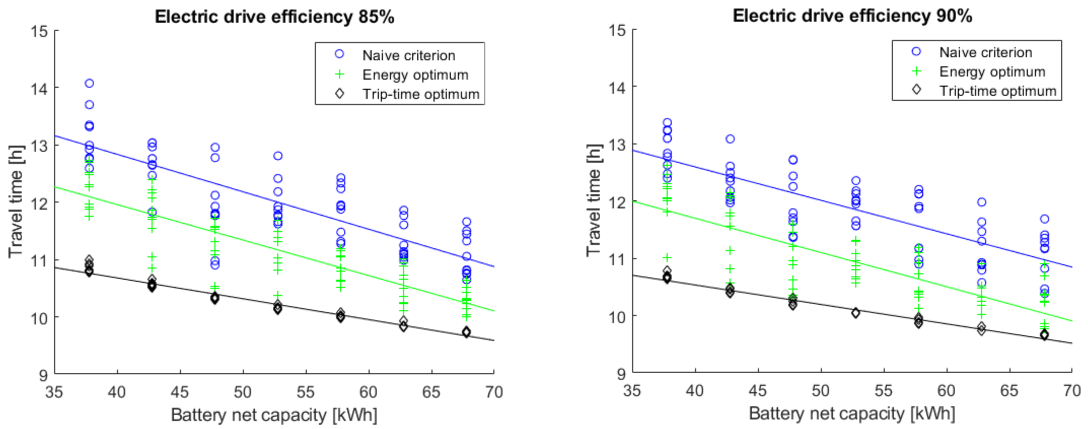


Figure 4 Overall travel time versus battery net capacity for the three considered strategies and for different values of electric drive efficiency. Results for an efficiency of 85% are displayed on the left, results related to an efficiency of 90% are displayed on the right. Linear fits of the data points are also displayed to visually illustrate the rate of variation of travel time with battery net capacity for all strategies.

trip time and energy consumption in comparison to the naive criterion. In particular, in Figure 3c, the simulation shows a minimum trip time of 10.5 hours, and this is achieved by optimizing the energy expenditure of the trip, which ultimately results in needing fewer stops for charging as illustrated by the background colormap. A battery with 50 kWh net capacity would suffice to achieve an overall trip time of 10.5 hours if the driver here was willing to accept 2 stops and was able to maintain a mean trip speed of slightly over 91 km/h (see blue cross in Figure 3c). Energy consumption in Figure 3d monotonically decreases with mean speed, as for the naive criterion, but at a higher rate.

The trip-time optimum strategy in Figure 3e and 3f shows again that the optimizer is able to find the best combination of alternative cruise speeds, charging stations and charging durations to improve performance in comparison to the naive criterion. Note that a narrower range of overall trip mean speed is observed in the results meaning that the optimizer mostly chose the average traffic speed v_{traf} rather than the alternative cruise speed v_{cruise}, and hence shows the need for adaptive cruise control systems. Supported drivers could achieve an overall trip time of 10.5 hours even with a smaller battery net capacity (i.e. 43 kWh) if they were willing to accept 4 stops along the journey and use ACC to maintain the recommended cruise speed profile (see blue cross in Figure 3e).

Once the willingness for charging stops and driver assistance systems has been established, it is possible to analyze the tradeoffs and calculate the potential advantages for battery sizing and ultimately vehicle cost. Reducing the battery net capacity from 60 kWh to 40 kWh would be a 33% reduction in battery capacity. Unsupported drivers would have to accept 3 stops to achieve this trip with this smaller battery capacity, and would require 12.5 hours if maintaining a trip mean speed of 89 Km/h (see green cross in Figure 3a). Even though it is only a 7% increase in overall trip time, the longer trip would likely not be acceptable. The energy optimum user would also have to accept 3 stops, but could achieve the trip in 12 hours if maintaining a trip mean speed of 91 Km/h (see green cross in Figure 3c). This would mean a 12% increase in overall trip time compared to the vehicle with a 60-kWh battery net capacity. However, energy savings compared to the other driver criterion would be minimal at that trip mean speed. The trip time optimum user willing to accept 4 stops would be able to carry out the trip in about 10.6 hours even with a battery net capacity of 40 kWh (see green cross in Figure 3e). This would only mean an increase of 7% for the overall trip time in comparison to vehicle with 60 kWh battery net capacity. A huge saving potential in vehicle price for a small loss of trip time.

Finally, an investigation of the electric drive efficiency parameter was conducted. The objective of this analysis was to assess the impact of foreseeable technological advancements to improve EVs powertrain efficiency on the smart driving and charging services proposed in this work. The results are shown in Figure 4 in terms of travel time with respect to battery net capacity. Each data point in the two graphs represents the result of a simulation experiment for a choice of v_{cruise} for a given battery net capacity, and a line fits the data points for each strategy to better show the trade-off. It is shown that the travel time of the naive criterion is the most sensitive to battery net capacity variation, for both values of electric drive efficiency. This sensitivity is only slightly reduced as the electric drive efficiency increases. The time gain for a unitary (in kWh) increase of battery net capacity is 3.9 minutes for an electric drive efficiency of 85%, and only slightly reduces to 3.5 minutes for a higher efficiency of 90%. The trip time optimum is nearly insensitive to battery net capacity, which indicates that significantly smaller battery net capacities are usable for long trips, and this advantage remains even for increased electric drive efficiencies, e. g. the travel time gain per unitary increase of battery net capacity drops to 2.2 minutes for an electric drive efficiency of 85%, and 2 minutes for an efficiency of 90%. Vehicles with smaller battery net capacities and lower drive efficiencies are available today. Implementing novel driver assistance strategies can alleviate range anxiety and even lead users to choose cars with smaller batteries. Finally, technological efforts to boost powertrain efficiency appear to be less urgent with regards to reducing travel time, and transition to electric mobility can be further promoted today with the right driving assistance.

Conclusions

To conclude, it has been shown that user’s expectations can theoretically be met for long-distance trips even with smaller battery capacities, but this requires novel eco-routing and eco-driving, as well as automatic speed control to support the acceptable execution of trips. Although there is no simple recipe to determine the optimal battery size, if the user’s acceptance/tolerance for charging stops during a long trip or the trade-off between trip time and energy consumption is known, then it is quite easy to determine the ideal battery capacity. Maintaining the recommended cruise speeds is best supported by state-of-the-art driver assistance systems, which can benefit overall trip time as well as easing driving load. The whole approach can therefore be made more user-centric and lead to more informed decisions about vehicle purchase, trip planning and driving style, and ultimately more affordable vehicles. An experimental campaign with a Fiat 500e is ongoing and shall be used for results validation. Future works will cover consideration of varying traffic conditions in the trip planning as the vehicle proceeds virtually along the route.

Acknowledgements

This project has received funding from the European Union's Horizon 2020 research and innovation program under Grant Agreement No. 824295 - CEVOLVER.

References

Alizadeh, M., Wai, H.-T., Scaglione, A., Goldsmith, A., Fan, Y.Y., Javidi, T., 2014. Optimized Path Planning for Electric Vehicle Routing and Charging. 52nd Annual Allerton Conference on Communication, Control, and Computing, pp. 25-32.

Brandes, H., Faye, I., Döge. V., 2020. Analysis of electric vehicle design and travel based on long trip capabilities. 8th Transport Research Arena.

De Cauwer, C., Faye, I., Sciarretta, A., Wahl, A., Manns, P., Tang, J., De Smet, F., El Baghdadi, M., 2022. Modular multi-level thermal and energy management strategies for optimal travel with passenger electric vehicles. 9th Transport Research Arena.

De Nunzio, G., Thibault, L., Sciarretta, A., 2017. Model-based ecorouting strategy for electric vehicles in large urban networks. SpringerBriefs in Applied Sciences and Technology, pp. 81–99.

De Nunzio, G., Ben Gharbia, I., Sciarretta, A., 2020. A Time- and Energy-Optimal Routing Strategy for Electric Vehicles with Charging Constraints. IEEE 23rd International Conference on Intelligent Transportation Systems (ITSC).

Liu, J., Peper, J., Lin, G., Zhou, Y., Awasthi, S., Li, Y., Rehtanz, C., 2021. A planning strategy considering multiple factors for electric vehicle charging stations along German motorways. International Journal of Electrical Power & Energy Systems, Volume 124.

Luo, Y., Feng, G., Wan, S., Zhang, S., Li, V., Kong, W., 2020. Charging scheduling strategy for different electric vehicles with optimization for convenience of drivers, performance of transport system and distribution network. Energy, Volume 194.

Morlock, F., Rolle, B., Bauer, M., Sawodny, O., 2019. Time Optimal Routing of Electric Vehicles Under Consideration of Available Charging Infrastructure and a Detailed Consumption Model. IEEE Transactions on Intelligent Transportation Systems.

Schoenberg, S., Dressler, F., 2019. Planning Ahead for EV: Total Travel Time Optimization for Electric Vehicles. IEEE 22nd Intelligent Transportation Systems Conference (ITSC).

Souley, S., Gillet, K., Colin, G., Simon, A., Nouillant, C., Chamaillard, Y., 2021. Optimization of the travel time of an electric vehicle with consideration of the recharging terminals. 16th IFAC Symposium on Control in Transportation Systems (CTS).

Treiber, M., Hennecke, A., Helbing, D., 2000. Congested Traffic States in Empirical Observations and Microscopic Simulations. Physical Review E, vol. 62, pp. 1805–1824.

Wang, Y., Bi, J., Guan, W., Zhao, X., 2018. Optimising route choices for the travelling and charging of battery electric vehicles by considering multiple objectives. Transportation Research Part D: Transport and Environment, Volume 64, Pages 246-261.