Energy Optimized Routing for E-Vehicles

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Abstract: The demand for routing tailored to electric vehicles will increase in the future due to the increasing number of users of electric vehicles. A growing number of people will face the same problem. What is the fastest energy-optimized route for my electric car to my destination? This paper describes the factors that influence the energy-optimized routing of electric vehicles. In particular, it shows how the influencing factors are used in routing and how they can be mathematically combines to obtain a general description. The influencing factors: topology of charging stations, energy consumption, topology of infrastructure, seasonal dependency and individual driving behavior are described. Furthermore, this paper shows the interactions between the factors. A new method for determining necessary edge weights is then presented mathematically in general. This weighting function was developed in the DLR project "Vehicle Intelligence and Smart Gearing" using empirical data analysis. The resulting equation can be applied iteratively to existing routing graphs to determine qualified edge weights. Existing current methods for routing are using the manufacturer information for the power consumption per 100 kilometers to generate a weight for their edges on the routing graph. Since consumption is only measured by the distance travelled, the shortest distance is always the one with the lowest energy consumption. Furthermore, in existing systems, the consumption is always constant for the same distance. This does not correspond to reality, since the range or consumption can increase or decrease with temperature differences. In addition, manufacturers of electric vehicles produce standardized consumption values that are generated under laboratory conditions and cannot be reproduced in reality. This paper shows how a single function can look like that mathematically combines different influencing factors. This result can be applied to existing routing systems to generate new, more qualified edge weights for energy-optimized routing.

1 INTRODUCTION

Rising sales of electric vehicles result in an increasing number of routing requests. In addition to conventional questions like the shortest and fastest route, the focus here is also on the most energy-efficient route (Rubel, 2018).

Figure 1 shows the half-year report on the development of electric mobility presented by the Center of Automotive Management (CAM) at the Bergisch Gladbach University of Applied Sciences. The experts around Prof. Dr. Stefan Bratzel analyse and assess the sales trends in important global automotive markets in the first half of 2018 and 2017. Despite the increasing sales figures shown above and the continuous improvement of the charging infrastructure, the challenge of e-routing will remain in the coming years. The characteristics of this route and the associated challenges of electro-mobility are far more complex than those of conventional vehicles. Both the range of the vehicles and the availability of possible charging stations are the central questions of route selection (Rubel, 2018). But there are other dependencies that influence the choice of route. This report defines and describes factors influencing the choice of route. Furthermore, it is shown how these are to be considered in a routing. Regional and seasonal differences as well as individual driving behavior are taken into account in order to create an energy-optimized route.

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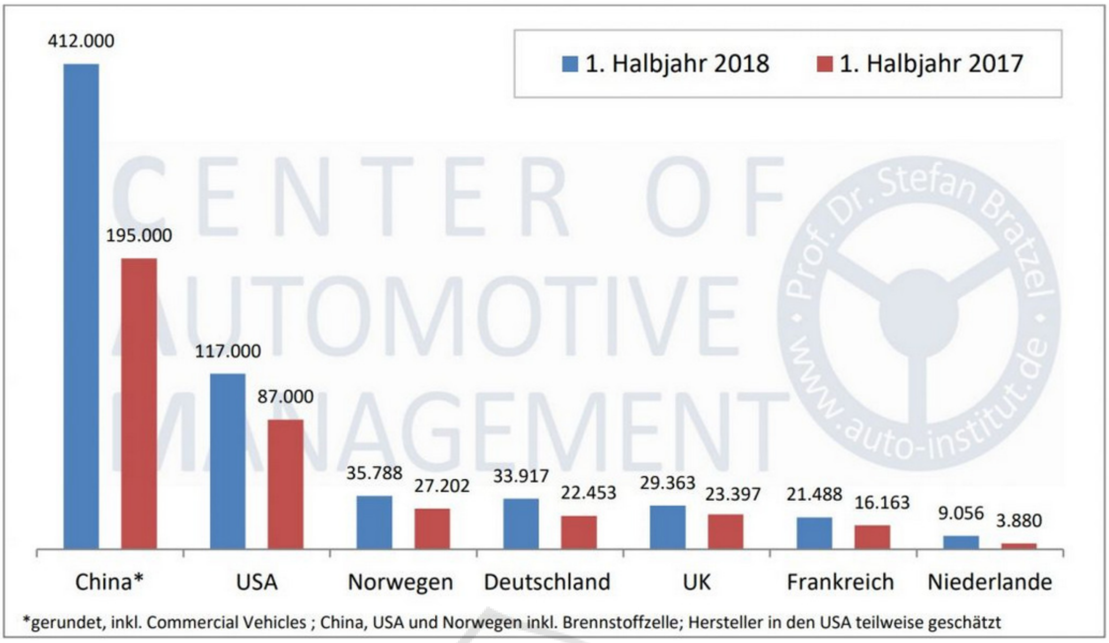

Figure 1. Sales trends for electric cars in key markets 2018/18 Hbj.1 (Bratzel, 2018)

2 INFLUENCING FACTORS

This chapter describes influencing factors when selecting a route for electric vehicles. Each of the following paragraphs describes a criterion for the range of electric vehicles.

2.1 Topology of Charging Stations

The range of an electric vehicle is arbitrarily large. Insofar as the vehicle is ready for operation and a charging station is within range. For longer journeys, the distribution of the charging stations is therefore very important for the choice of route. It is essential to consider any side effects of the route selection. The lack of charging infrastructure can be fatal, especially for less experienced users. For example, a route to a less serviced area can often be found at charging stations and the routing request would then be completed. However, the remaining state of charge of the vehicle may no longer be sufficient to reach the next charging station. In this case, the suggested route should draw attention to the problem that no charging station can be reached from the destination.

2.2 Energy Consumption

The consumption of electric vehicles is expressed in standard values and is not uniquely defined for manufacturer or type (Hiller, 2018). For reasons of increased sales, it is conceivable that strongly optimized boundary conditions will be used as the basis for the calculations. For the small car Nissan Leaf, for example, this is 15 kWh per 100 kilometers, for the electric Golf VW gives 12.7 kWh (Hiller, 2018). These standard values often do not correspond to the real consumption of these vehicles. The following is an overview of the standard values for the vehicles with the highest sales volume according to the CAM study (Bratzel, 2018).

Table 1. Consumption of electric vehicles (Bratzel, 2018).

Vehicle	Manufacturer Consumption / 100 km
Tesla Model S P90D	22 kWh
Ranault Zoe	14,6 kWh
Nissan Leaf	15 kWh
Mitsubishi-MiEV (FL)	13,5 kWh
BMW i3	12,9 kWh
E-Golf	12,7 kWh
Mercedes B-Class ED	16,6 kWh

Table 1 shows the values according to the manufacturer's own specifications. In addition to these figures, independent methods according to WLTP and NEDC promise more precise figures for actual consumption. Worldwidmonized Light(-Duty)

Vehicles Test Procedure, WLTP for short, is the new standard test procedure that is intended to provide realistic data on the fuel consumption of electric vehicles and other passenger cars. The NEDC (New European Driving Cycle), which has been in force since 1992 and is not very accurate, will be gradually replaced by September 1, 2018. Germany is regarded as a global pione Hareer in the changeover. The source (Kammerer, 2018) shows the differences between the test cycles and how the new WLTP value will affect the future. The fact is that these measurements and efforts will not be able to withstand a real measured value and experience, as further criteria influence consumption and the associated range (Kammerer, 2018).

2.3 Topology of Infrastructure

The construction of the roads and their gradients also result in considerable differences in the choice of route. As can be seen from the publication "Topographic maps for greater range of the ECar" (Spanik, 2018). In the BMW i3, for example, the fuel consumption values per 100 km are almost twice as high when driving uphill (Spanik, 2018). It also depends on the vehicle how much energy can be recovered when driving downhill. The exact creation of a database for the construction of the road network is therefore essential for choosing the right route. Especially with an energy-optimized routing, height differences have to be considered.

2.4 Seasonal Dependency

The seasonal dependency of the route choice refers to the different consumption of energy in the seasons. The electrical consumption for comfort components in the vehicle, such as air-conditioning systems, is usually higher in seasons such as winter and summer. Tesla models, such as the Model S, heat not only the interior, but also the battery if necessary. If the battery is cold, kilometers are lost that are more than the lost heat output (Becker, 2018).

The ADAC tested the loss in winter on a Mitsubishi i-MiEV as an example and came to the following verdict (Butz, 2018):

At speeds around 100 km/h, the relative losses in range are still comparatively low:

- At 20 degrees, the electric car can travel 91 kilometers.
- At 0 degrees, it can cover 82 kilometers.
- At minus 20 degrees it's still 70 kilometers.

A much higher loss of range, on the other hand, can be seen at speeds of 30 km/h:

- At 20 degrees, the electric car covers 188 kilometers.
- At 0 degrees it achieves 93 kilometers.
- At minus 20 degrees it's still 68 kilometres.

Inner cities at 50 km/h are therefore likely to suffer greater losses in range due to seasonal influences than on the motorway. This in turn influences the choice of route.

2.5 Individual Driving Behavior

The individual driving behavior of individuals also affects the fuel consumption or range and the associated route selection of an electric vehicle. Features such as time and driving style play a role here. If, for example, a restrained driver drives to work with a prudent driving style, it will consume less electricity than a notorious speedster that accelerates a lot. Furthermore, a prudent driver can also become a high consumer if he is under time stress and wants to reach his destination quickly. Similar rules apply here as with conventional combustion engines in order to increase the range: (Greenfinder, 2018)

- Quiet and prudent driving
- Drive in anticipation
- Avoid strong accelerations
- The lower the speed, the lower the energy consumption

This behavior is still encouraged by some manufacturers. With different driving modes, such as Comfort, EcoPro and EcoPro+, as is possible with the BMW i3, for example. In electric cars, the so-called recuperation effect takes effect. This means that some of the energy generated by the braking effect of the engine is fed back into the battery. The energy recovered in this way extends the range of the electric car. If, on the other hand, you step too hard on the brake, energy is also generated, but in this case, as with combustion engines, it is released more in the form of warmth and can no longer be used as well (Greenfinder, 2018).

3 ENERGY-OPTIMIZED ROUTES

In this chapter, the previously described dependencies for energy-optimized routing for e-vehicles are put into context. It also describes how influencing factors can influence each other. Furthermore, the procedure for implementing an energy-optimized routing is described.

3.1 Interactions

In order to find the best possible energy-optimized route, it is not sufficient to optimize the criteria for route enquiries in terms of range mentioned in Chapter 2. The topology of the charging stations does not initially play a role in energy-optimized routing, as this does not influence energy consumption. However, if this criterion is not met in sufficient numbers within the start/finish relationship, no routing is possible. Therefore, the existence of a charging infrastructure is absolutely necessary for the consideration of an energy-optimized route.

The data on energy consumption could also not be used for energy-optimized routing. As Section 2.2 shows, the data on the standard values of the individual vehicles are not very accurate. If these values were used to determine a low-consumption route, the shortest route would always be found. Sections 2.3 to 2.5 show that the shortest route does not have to be the most energy efficient.

Nor can it be generalized that, as shown in section 2.3, a flat straight route is more energy efficient than a winding route. On a very twisty route that has no vertical meters, section 2.5 may be more effective than section 2.3. The topology of the network therefore requires the driver to be slower, more prudent and more forward-looking. Furthermore, section 2.4 shows that the weather can also influence the most energy efficient route.

3.2 Procedure

The theoretical implementation of an energy-optimized routing for electric vehicles is only possible with a sensible weighting of the influencing factors. The following influencing factors can be derived from the literature: (Bratzel, 2018) (Kammerer, 2018) (Spanik, 2018) (Becker, 2018) (Butz, 2018) (Greenfinder, 2018)

- Existence of charging infrastructure
- Travel speed
- Structure of the road network (angle of vertical meters, angle between edges)
- Outside temperatures
- Driving behavior
- Energy consumption of comfort components

The weighting of the influencing factors is based on a percentage distribution of the empirical values described in the literature and is not supported by empirical data. Table 2 below shows the weighting ratio for the influencing factors.

Table 2. Weighted influencing factors.

Influencing factor	**Influence in percent (%)**
Existence of charging infrastructure	-
Travel speed	30
Construction of the road network	30
Outdoor temperatures	20
Driving behavior	15
Comfort components	5

A routable graph is created according to this model. The graph evaluates a node and edge topology according to the following algorithm. This applies to all edges (n) in a routable graph. The individual weight of the influencing factors is determined with points from 0 to 100. The points are then weighted in percent based on their influence. The lower the score of the individual influencing factors, the lower the resulting edge weight for routing. Thus the value 0 is to be understood as optimal and 100 as worst value for the individual evaluation.

1. The velocity on the edge (n) is linearly assigned to the point values from 0 to 100, where applies:

$$f(x) = \begin{cases} x & \text{if} \quad 0 \leq x \leq 100 \\ 100 & \quad\quad x > 100 \end{cases} \{ x \in \mathrm{N} \cup \{0\}\} \tag{1}$$

2. Slope of the edge (n) in $f(x) = \frac{\text{height (m)}}{\text{length (m)}} * 100\,\%$ (2)

Linear equation for the determination of points: y = m*x +n

$$\mathrm{m} = \frac{1}{2} \tag{3}$$

$$\mathrm{n} = 50 \tag{4}$$

$$\mathrm{x} = \left(\frac{\text{height (m)}}{\text{length (m)}} * 100\right) \tag{5}$$

$$\mathrm{f(x)} = \begin{cases} 0 & \mathrm{x} < -100 \\ \frac{1}{2} * \left(\frac{\text{height (m)}}{\text{length (m)}} * 100\right) + 50 & \text{if} \quad -100 \leq \mathrm{x} \leq 100 \\ 100 & \mathrm{x} > 100 \end{cases} \tag{6}$$

The result of this equation is that at a gradient of 45 degrees or 100 percent, the maximum worst value is assumed to be 100, while at a gradient of 45 degrees, the maximum best value is assumed to be 0.

3. The outside temperature is assumed to be optimal at 20 degrees. Values left and right of x = 20 worsen the scoring again. With less than minus 20 degrees and more than +60 degrees the maximum worst value of 100 is reached (Butz, 2018).

$$f(x) = \begin{cases} 100 & x < -20 \\ 0{,}05 * (x - 20)^2 \quad \text{if} & -20 \leq x \leq 60 \\ 100 & x > 60 \end{cases} \quad (7)$$

The function corresponds to the illustration of a parabola shifted by 20 on the X axis and compressed by 0.05.

4. The driving behavior is classified into 5 levels, which are shown in table 3:

Table 3. Driving behavior point table.

Behavior	Points
Looking foresighted	0
Less foresighted	25
Average	50
Less aggressive	75
Aggressive	100

The driving behavior must be defined by the user himself before routing. In the case of larger amounts of data, a mechanical evaluation using "Deep Learnin" is conceivable. For this purpose, the individual driving behavior is classified by a neural network.

5. The use of comfort components is listed in table 4 and the totals of the points are then added.

Table 4. Points for comfort components.

Comfort components	Points
Air conditioning	50
Seat heating	30
Light	15
Radio	5

The comfort components used must be specified during routing. The selection is implemented via a check box, the sum of which is the weight for this influencing factor.

6. The last influencing factor is the presence of a charging infrastructure during and after the journey. For this purpose, the energy consumption described in Chapter 2.2 according to WLTP, if not available according to NEDC or as a last possibility the manufacturer's data, is taken to 100 km. Due to the inaccuracy, the value is increased by 20 percent. The algorithm determines the consumption after each edge and searches for a charging station if the vehicle has only 20 percent of its load left. In addition, at least 10 percent of the load must still be present at the destination so that the driver can safely leave the destination again. If these criteria cannot be met. Then the lack of the charging infrastructure is to be regarded as a KO criterion and no route to the destination can be found.

On the basis of the points to be determined for each influence criterion, the weight for the edge is to be determined by means of the following weighting function. For a = speed, b = structure of the road network, c = outside temperatures, d = driving behavior and e = comfort components.

$$f(x) = (a * 0{,}3) + (b * 0{,}3) + (c * 0{,}2) + (d * 0{,}15) + (e * 0{,}05) \quad (8)$$

Each influencing factor can only take values between 0 best and 100 worst. Thus, the weight of the edge is defined in the closed interval from 0 to 100. The new weight of the edge is taken into consideration during routing and results in the most energy-optimal route.

4 CONCLUSION

The demand for energy-optimized routes for e-vehicles increases with the number of vehicles sold. Conventional questions about the fastest or shortest route are more sufficient for the user. Especially because of the often still short range of electric vehicles, the question of the lowest possible consumption is at the forefront of the considerations. Optimizing fuel consumption means increasing the range.

Chapter 2 describes dependency factors for this question. Each criterion is decisive for the choice of route. The necessity of the inclusion is explained in the respective sections. This shows that it is not only the infrastructure that can influence the most energy-efficient route. Environmental influences and individual factors also play a role.

Chapter 3 compares the dependencies between the influencing factors. For example, bad weather influences one's own driving behavior towards a quieter driving style. This in turn has a positive effect on the choice of route. It also shows that not all influencing variables may be weighted equally. For example, the difference in altitude of a route from start to finish has a greater influence on the most energy-efficient route than driving with or without air conditioning.

Section 3.2 describes the weighting for the influencing factors as well as the functions for determining the point values for each criterion. The algorithm described in this chapter can be applied to a routable graph to demonstrate energy optimized routing for an electric vehicle.

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