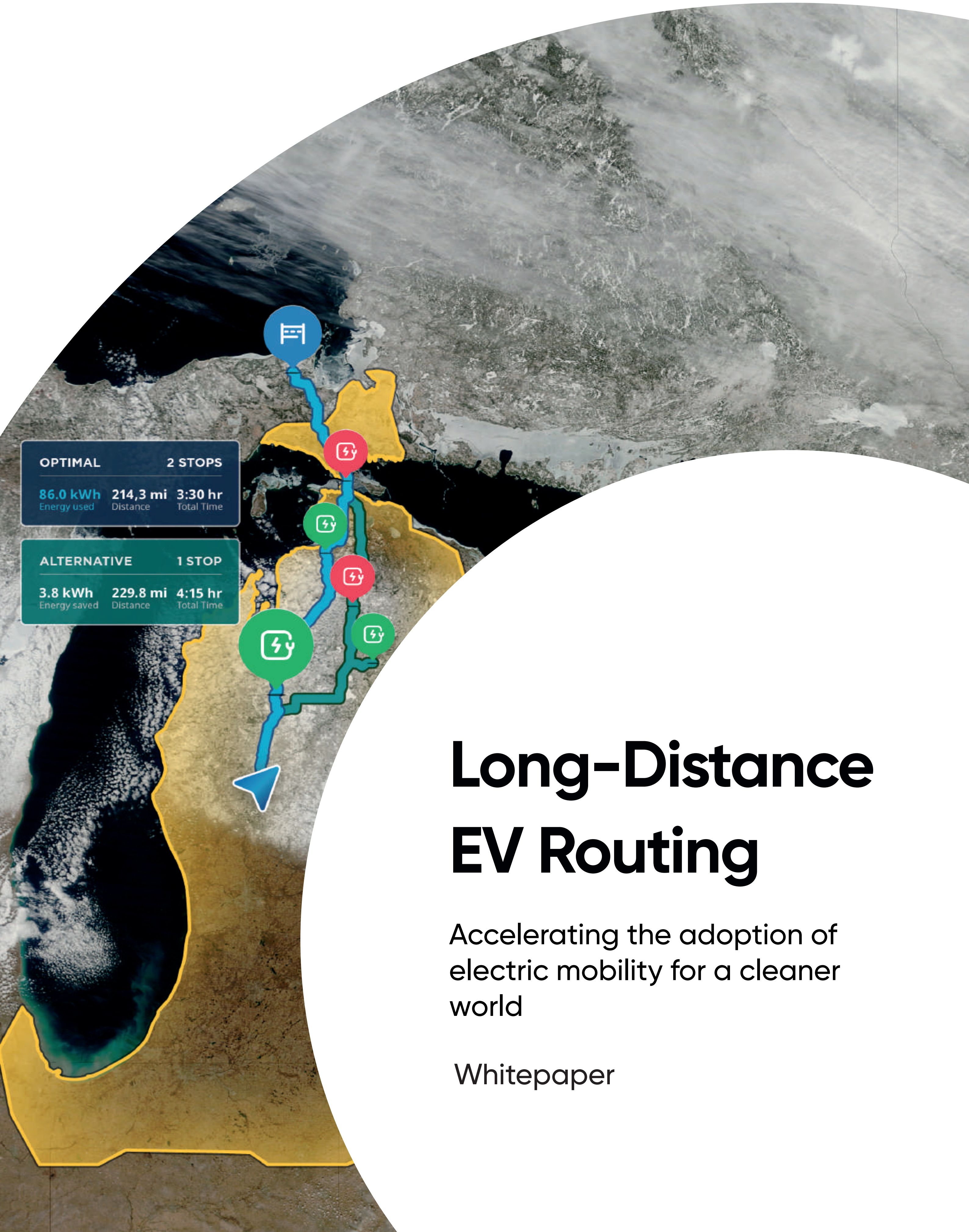

Long-Distance EV Routing

Accelerating the adoption of electric mobility for a cleaner world

Whitepaper

Introduction

The road transport sector contributes significantly to the overall CO_2 emission. Although production and disposal of an electric vehicle (EV) today is less environmentally friendly, it is proven that the overall life-cycle CO_2 emission for EVs is significantly less, especially when moving to renewable energy sources. And with TomTom's Long-distance EV Routing, we enable drivers to get to their destination quickest, no matter the range.

The need to reduce CO_2 emission has led to government targets to phase out new sales of internal combustion engine (ICE) vehicles. Automobile manufacturers follow this trend by making pledges to halt or drastically reduce the production of ICE vehicles in the next decade.

From the consumer's perspective, there are still some barriers to overcome. Although EVs already have lower operational cost, the retail price of an EV is still relatively high. The good news is, due to declining cost of EV batteries, prices of EVs will drop in the coming years, eventually becoming cheaper than its ICE counterpart .

The driving range of EVs is increasing, but the range indication is often highly unreliable. Next to that, charging stations sprout like mushrooms in Western Europe and the United States. However, charging stations differ in charge levels, for charging there is no single payment method and in general the market is fragmented. This leads to range and charging anxiety; two major psychological barriers hampering large-scale adoption of electrical vehicles by drivers. TomTom's location technology can help provide accurate range prediction and smart selection of charging stations. In this whitepaper, we explain how.

[1] europarl.europa.eu/news/en/headlines/society/20190313STO31218/co2-emissions-from-cars-facts-and-figures-infographics

[2] theicct.org/sites/default/files/publications/update-govt-targets-ice-phaseouts-jun2022_0.pdf

[3] firstpost.com/tech/auto-tech/evs-are-the-future-a-list-of-all-carmakers-who-have-decided-to-phase-out-ice-vehicles-and-go-electric-9744401.html

[4] visualcapitalist.com/electric-vehicle-battery-prices-fall

Accurate range prediction

The driving range of EVs depends on the vehicle's battery capacity and consumption. The consumption over time is not constant, but heavily influenced by all sorts of dynamics while driving, as depicted in Figure 1. That is why the advertised range of an EV is often not in-line with reality. The range prediction in vehicles nowadays is also often inaccurate, for example the indicated range can drop twice the distance you travel. When the vehicle indicates an unrealistic range, drivers cannot use this figure to be sure to reach their destination and face range anxiety. For professional drivers, charging longer and more often than necessary leads to loss of time and money for their business.

To accurately predict range, TomTom uses a physical consumption model. Vehicle data combined with location data are the inputs to our model, see Figure 2. The battery capacity and state of charge (SoC) determine the remaining charge of the battery. Other vehicle characteristics determine the consumption while traversing the road network, such as the consumption curve and consumption efficiency coefficients to model the kinetic effects. Vehicle parameters are not static. They can change over time or even during a trip, for example to set different consumption values when setting the vehicle to eco-mode or compensate for battery aging by adapting the battery capacity. Combined with map data and real-time traffic information the consumption is calculated for a given trip. Slope, curvature, historic speed profiles, traffic jams, junctions: all these aspects are considered while predicting consumption and range. For example, by combining downhill efficiency of the vehicle together with slope data, energy recuperation is considered.

Range accuracy is a KPI of our product. Range accuracy compares the predicted remaining energy with the actual value during a trip. By working closely together with OEMs, we integrate and tune our model. By measuring we prove that we accurately predict range. Going forward our ambition is to get close to 0% error by learning and adapting range prediction based on this KPI.

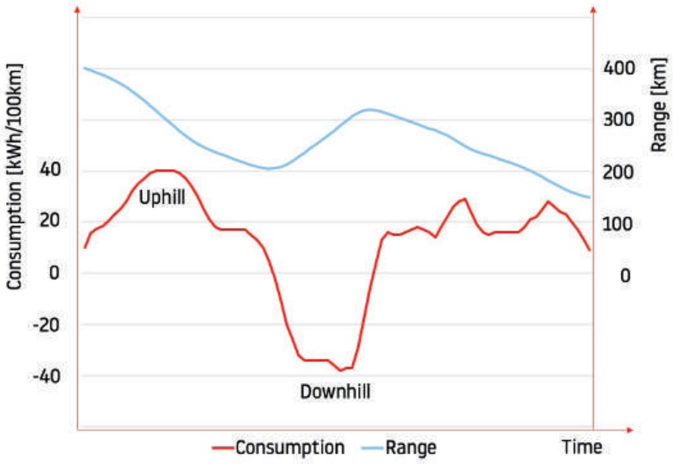

Figure 1: Consumption and range are dynamic. They change based on many different variables such as slope and the vehicle's efficiency to recuperate energy when going downhill.

For professional drivers, charging longer and more often than necessary leads to loss of time and money for their business.

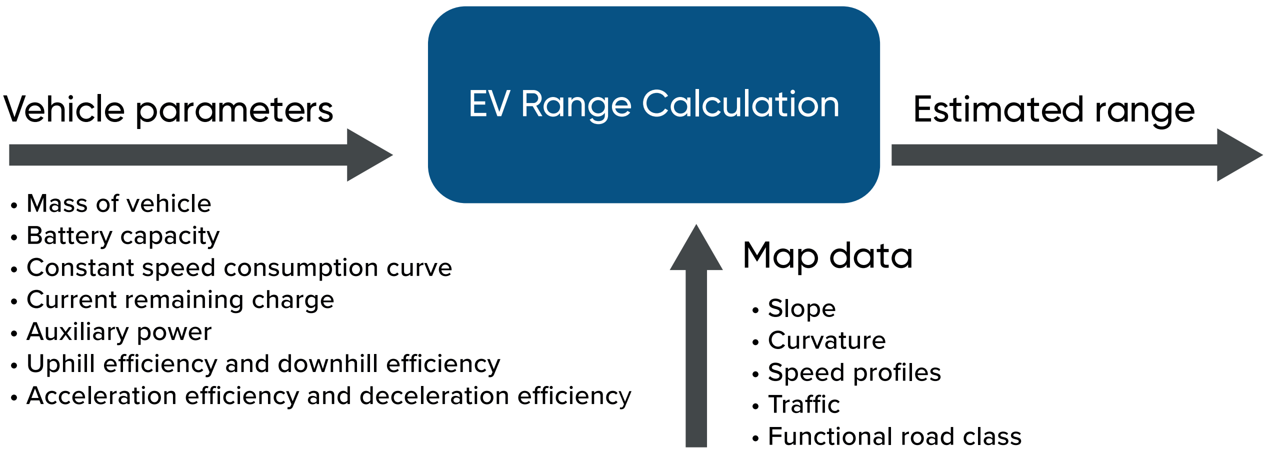

Figure 2: Input parameters to the EV range calculation model providing the estimated range.

Smart selection of charging stations

Whether a vehicle has a long range or not, at some point your destination will be out of range. Given the fragmented charging landscape, it can be a true hassle to find a charging station! Tesla has solved this to some extend by rolling out its own charging infrastructure. For most other OEMs today, this is not a reality and drivers face many questions when trying to find a charging station. How long does it take to charge? How much does it cost to charge? Can I pay? And when you finally arrive at your chosen charging station, you may find it is out of order.

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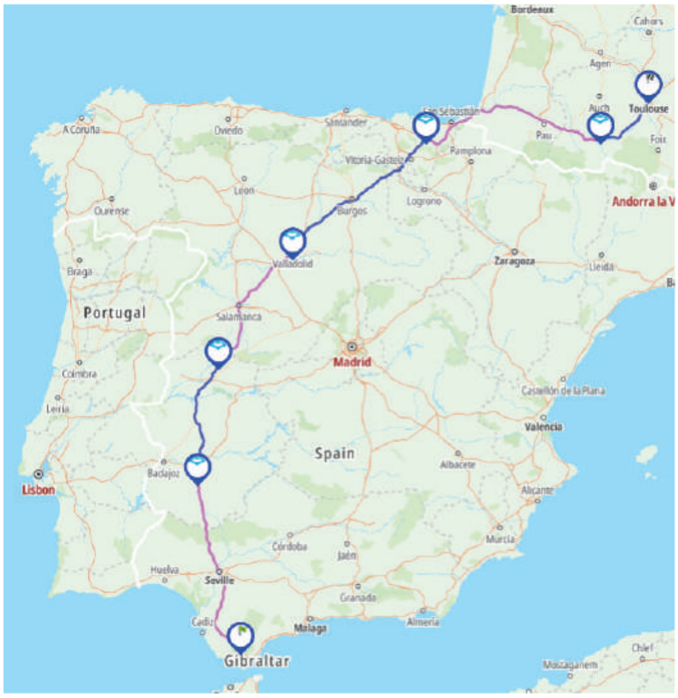
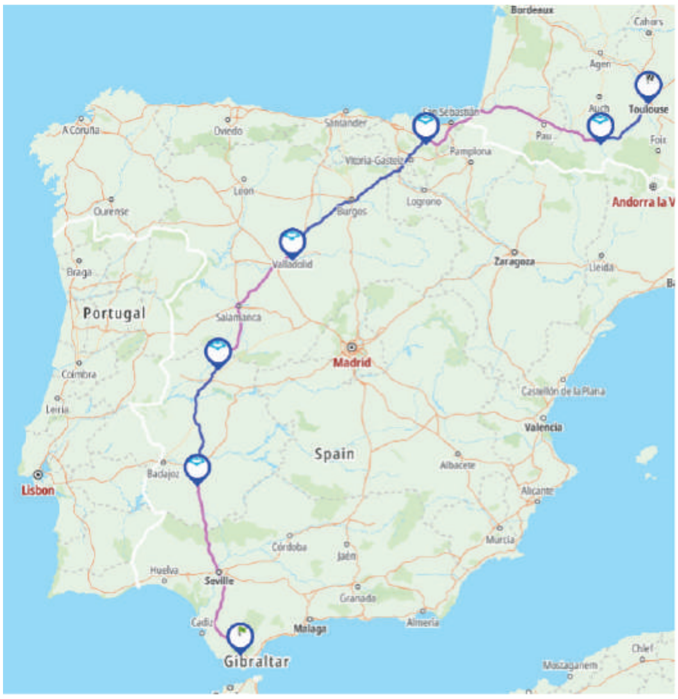


The fastest combustion route from Gibraltar to Toulouse with charge stops along that route.

A challenging problem

Computing the optimal route with charging stops is a challenging problem for different reasons. First, if you go on a longer trip you really want fast chargers, as the slow ones may take hours to charge. Even though in some countries there are already numerous charging stations, only 5% of chargers are fast chargers. Consequently, the optimal EV route might take you via a very different path compared to that of an ICE route, whilst reducing the charging time considerably, as shown in Figure 3. Nevertheless, if there is no fast charger within the range of the vehicle or if the detour would be too long, you still want to use a slow charger; but then charge there only the amount needed to reach the next fast charger. Hence, a routing algorithm must consider a huge number of different combinations when computing the optimal route.



The optimal route for the same trip for a certain EV minimizing overall travel time by using faster charging stations.

And then: How long do you have to charge at a charging stop to minimize the overall charging time? To answer this, the charging power must be known, which is influenced by many factors such as the power of the charging station, the type of the vehicle, and the temperature of the battery. In addition, the power is usually higher when the battery is empty, and it is quite low when the battery is nearly full. This is illustrated with the charge curve in Figure 4. It shows the battery charge level along a trip with one charge stop. When we start charging, the battery level increases quickly but flattens over time. Given the varying charging power, computing the optimal charge level for each charge stop of a longer trip is already challenging as there is an infinite number of potential solutions indicated in the figure below by the array of curves starting after charging.

As shown for a single charge stop above, when charging too little, the destination (or the next stop) cannot be reached (grey curves in the Figure 4). If charging too long, you spend additional time charging that is not required and is also ineffective as the charge power drops when charging more. While the solution is simple for a single stop, it becomes complicated for multiple stops: you may arrive at a stop with any charge level (depending on what we decide to charge on the previous stop) and you actually prefer to charge longer on faster chargers to minimize the total charging time.

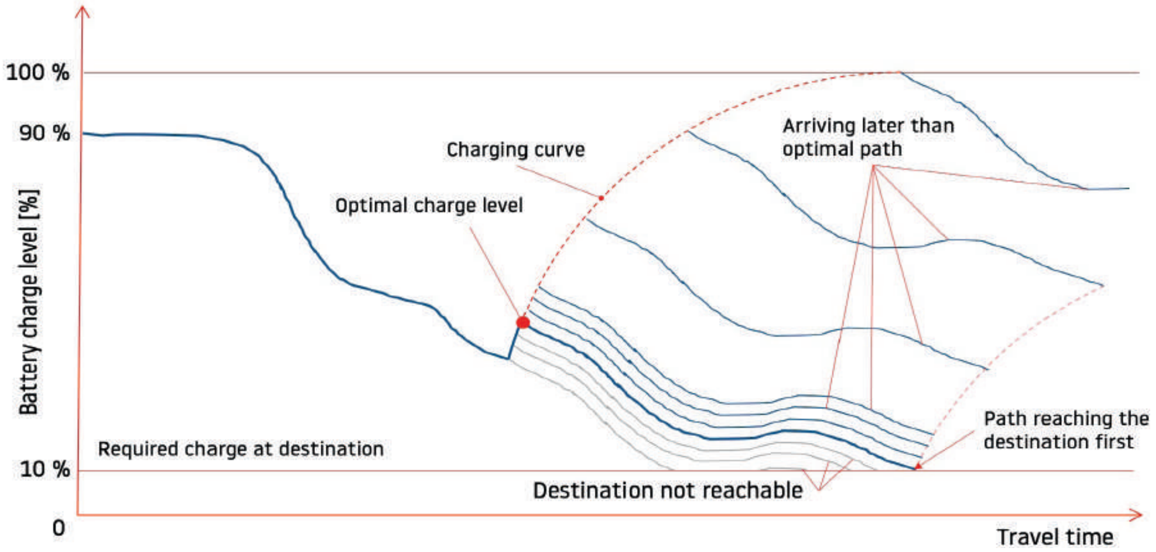


Figure 4: Battery charge level over time for a trip with one charge stop. The optimal path is shown in bold. While driving, the charge level decreases until charging at a charge stop. The charge curve is steep in the beginning and flattens towards the end. After charging, the trip can be continued with any selected charge level indicated by an array of curves after charging. The optimal charge level is determined such that the destination can just be reached to not loose time with charging if not needed.

And then: How long do you have to charge at a charging spot to minimize the overall charging time?

There are several other factors that also must be considered, such as varying travel times and consumption due to traffic, or various factors influencing consumption such as load of the vehicle, the weather, or preferred driving speed. Solving such a complex problem for each trip would take a huge amount of time, but of course you want an immediate response when planning a long trip with your vehicle. So, the ultimate challenge in EV routing comes from the complexity of the problem together with tight runtime requirements.

Our solution: Pre-processing

At TomTom, we solve this problem by precomputing frequent paths through the route network to which we connect the charging stations. The result is a much smaller EV routing graph that contains all information needed to later compute a sequence of charge stops for all kinds of vehicles with changing load and varying environmental conditions. Such a precomputation is a challenge by itself as it must be fast enough to make sure new charging station data can be without much delay. It must also result in a graph that is sparse enough to enable fast route computations while not sacrificing route quality.

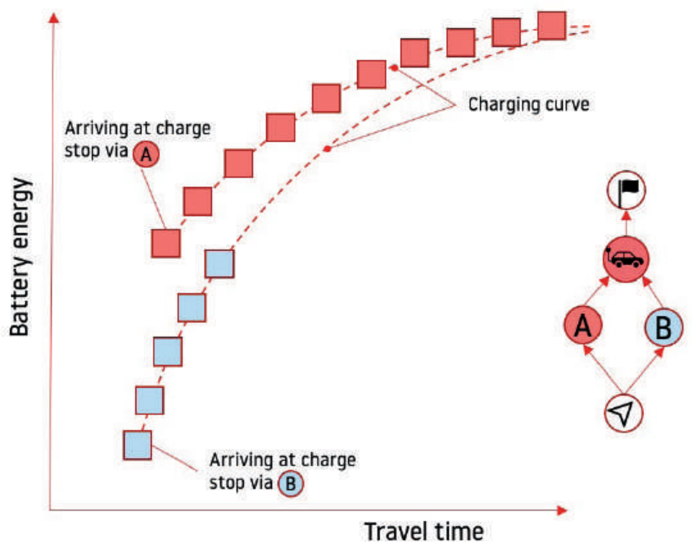


Figure 5: Pareto front for a charge park of a simplified graph (right side). The path via A, has lower consumption but is slower, resulting in more energy in the battery when arriving. The path via B is faster but consumes more energy. When arriving via A, we add points to represent charging up to a full battery. When arriving via B, we only add points for lower charge levels as for higher levels the path via A results in lower travel time.

Optimizing for time and energy

Given a precomputed graph, we compute a route on that graph that takes charging with varying charging characteristics of different vehicles into account. Here we use a variant of Dijkstra's algorithm that allows for optimizing multiple objectives – in our case travel time and energy consumption. Traversing the nodes of the graph, we compute accurate battery charge levels for each visited node using our range prediction presented above. We store in each node the travel time and battery level for each possible path to that node. However, we keep only those that are better, i.e., if arriving earlier or if arriving with more energy in the battery. The result is called a pareto front - the pareto-optimal set of paths to reach a node.

For charge parks, we also add points to the pareto front to represent charging as shown in Figure 5 when arriving at the charge park via A, we add points (following the charge curve) up to a fully charged battery. The path via B is faster than via A but consumes more energy. When arriving via B, we also add points for charging but discard points for higher charge levels as those take longer than charging to the same charge level for the path via A.

The pareto front of a node is propagated to each of its neighbours in the graph: we assume that we start driving to the neighbours for each point in the pareto front and adjust travel time and battery level according to the path to the neighbour. This way we then build the pareto fronts for the neighbour nodes. This is repeated until reaching the destination.

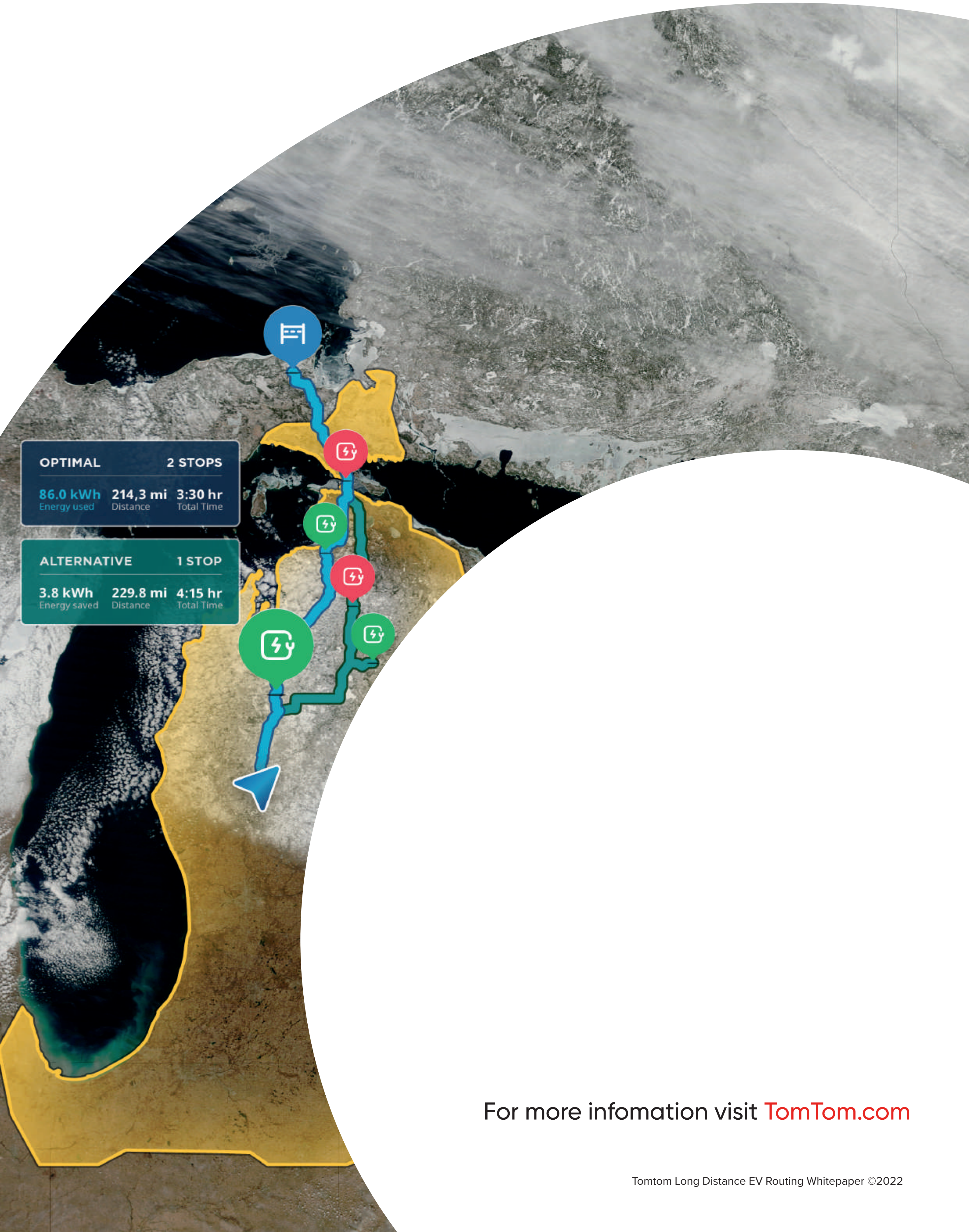
The output of the algorithm is a route via one or more charging stations that takes the current traffic situation into account and minimizes the overall travel time including time for charging. It tells you when you will really arrive at your destination and provides information about the exact energy amount you should charge at each stop to get the best travel time. But of course, if you decide to stay longer for a stop to enjoy your lunch, your route will be adapted to the new situation such that the remainder of your journey is optimal given the increased battery charge and the updated traffic situation.

Conclusion

Electric mobility is an important step towards a cleaner world with less CO_2 emission. TomTom's location technology can help accelerate the adoption of electric mobility. There are two psychological barriers that EV drivers face: range and charging anxiety. TomTom's Long-Distance EV Routing provides solutions to take away this anxiety. First, by providing accurate range prediction and second by smartly selecting charging stations along your route when needed.

Selecting the best route including charging stations is a challenging problem. By precomputing the options, we calculate EV routes within seconds. TomTom provides EV routes that get you to your destination the fastest, including charging, by optimizing for time and energy. The algorithm leverages our rich map and traffic content as well as information from the vehicle and its surrounding.

TomTom continues to innovate and will bring more dynamic content in the mix to support further use cases. This way we ensure drivers are proposed the most convenient charging stations required to reach their destinations fast and hassle free. This helps more people overcome anxiety and accelerates adoption of electric mobility.



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