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Abstract

Critical success factors for the efficient use of electric trucks are the operational range and the total costs of ownership. For both range and efficient use, power consumption is the key factor. Increasing precision in forecasting power consumption and, hence, maximum range will pave the way for efficient vehicle deployment. However, not only electric trucks are scarce, but also is knowledge with respect to what these vehicles are actually technically capable of. Therefore, this article focuses on power consumption and range of electric vehicles. Following a discussion on how current research handles the mileage of electric vehicles, the article illustrates how to find simple yet robust and precise models to predict power consumption and range by using basic parameters from transport planning only. In the paper, we argue that the precision of range and consumption estimates can be substantially improved compared to common approaches which usually posit a proportional relationship between energy consumption and travel distance and require substantial safety buffers.

Keywords

Electric trucks · Power consumption · Range estimation · LASSO regression


8.1 Introduction

Research on electrified delivery has gained substantial momentum over the past decade as companies from various industries try to reduce their carbon footprint in transport. Urban logistics seems like a perfect field of application for electric trucks since it allows delivery runs without causing tailpipe nitrogen oxides or particulate matter emissions and helps to curb the problem of traffic noise (Pelletier, Jabali, and Laporte 2016). From a business perspective, it also makes perfect sense to deploy electric trucks in urban areas since usual delivery runs are both rather predictable and short enough to allow the use of range-limited vehicles (Quak and Nesterova 2018; Teoh 2018). Range is acknowledged as the dominant limiting factor for electric vehicles, and several sophisticated models on this topic have been proposed (Zhou, Ravey, and Péra 2019). But since applying the latter requires a plethora of different input variables, the continuous availability of fine granular data or even both (Tseng and Chau 2017), this article takes a different perspective on this issue. Instead, it is investigated to which degree basic information from vehicle dispatching can be used for range prediction with higher precision than widespread naïve approaches assuming a direct proportional relationship between energy consumption and travel distance.

This contribution is organized as follows: As a first step, the relevance of precise range estimations for fleet and operation managers and why range/energy consumption belongs to the key variables to promote electric vehicles are illustrated. A subsequent literature overview shows how energy consumption and vehicle range are usually handled, respectively. It is argued that there is a strong need of range estimation models for which input data is easily available. These models have to be usable by decision-makers with access to basic route optimization tools and allow a more precise estimate than the frequently used simple albeit imprecise rule of three. Using real-world data from the research project “EN-WIN” of Fraunhofer IML combined with a regression approach, different consumption/range estimation models are discussed and benchmarked with the widespread naïve approach.

Funded by the German Federal Ministry of the Environment, Nature Conservation and Nuclear Safety, grant no. 16EM3118, the EN-WIN consortium consisting of Technical University of Berlin, Fulda University of Applied Sciences, Florida-Eis Manufaktur GmbH, Ludwig Meyer GmbH & Co. KG, BPW Bergische Achsen KG and Fraunhofer Institute for Material Flow and Logistics (lead) assessed options to facilitate and improve the deployment of electric trucks using real-world energy consumption data.

8.2 The Need for Precise Energy Consumption and Range Estimation

As profit-oriented entities, companies are inclined to electrify substantial parts of their fleets only if two preconditions are met:
There is an electric vehicle which is technically capable to substitute the currently used combustion-powered vehicle, especially in terms of range and payload (Felipe, Ortuño, Righini, and Tirado 2014).

The expected total costs of ownership (TCO) for the electric vehicle are lower than the TCO for the currently used combustion-powered vehicle (Camilleri and Dablanc 2017).

In case a fleet manager agrees to both aspects and acquires and deploys a certain electric truck, two important operational questions arise in addition: “How to make sure that the vehicle actually provides an ongoing advantage in total ownership costs?” and “How to make sure route planning does not exceed the electric range?”

It is evident that detailed and reliable knowledge about realistic vehicle ranges is decisive for the adoption and ongoing (i.e. economically viable) use of electric trucks (Erdelić and Carić 2019). As Fig. 8.1 illustrates, logistics companies have strict requirements when it comes to vehicle payload and range.

Vehicle batteries are a payload reducing factor, while, at the same time, they represent a key determinant of vehicle range (Pelletier, Jabali, and Laporte 2016). Range, however, does not only depend on battery capacity alone but also on the actual use case (typical routes, road network, stop frequency, ambient temperature, etc.) which makes it questionable to posit a proportionality of energy consumption and trip length. Therefore, a fleet manager must carefully consider the trade-offs between payload and range requirements (Stütz, Taefi, and Fink 2018). While payload is ex ante known from specification documents, consumption, and consequentially range, is not. When companies consider the purchase of electric vehicles, they need to assess their economic potential. For the latter, the expected electricity consumption is a key TCO driver and is depending on the actual use case. This illustrates that oversimplified or imprecise information concerning the

![Fig. 8.1 Interrelationships between vehicle battery, vehicle requirements, use-case, and TCO](image-url)
efficiency of an electric truck will directly affect business case considerations in various ways (cf. Fig. 8.2).

- **On the tactical level**, fleet managers can overestimate vehicle range, thereby paving the way for overambitious electrification in that sense that the organization has not yet acquired the necessary knowledge and experience to use the electric trucks. Opposite, too low efficiency estimates will lead to an exclusion of suitable vehicles. From a cost perspective, imprecise consumption figures will, likewise, lead to a situation in which cost-effective vehicle will appear as uneconomical and vice versa (Taefi, Fink, and Stütz 2016).

- **On the operational level**, imprecision will either lead to over- or underestimation of vehicle range. Either case has negative business impacts as vehicles actually run out of energy while en route or regularly return to the depot with a substantial battery charge remaining, thus wasting parts of their potential to reduce operational costs (Stütz et al. 2016).

This illustrates that reliable use case-specific and credible knowledge about real-world power consumption and range is one of the most critical issues to address in order to promote the broad adoption of electric vehicles. Literature is following different paths to integrate this crucial variable.

(a) **Power consumption is regarded as a set of given values taken from external sources.** This seems expedient when the actual consumption and vehicle performance are not the focus of research, for example, when extending vehicle routing models (VRP) to integrate the specific properties of electric vehicles. However, when these models are parameterized and solved, the context-specific and route-dependent consumption becomes an issue (Erdelić and Carić 2019; Erdoğan and Miller-Hooks 2012).

(b) **Relative power consumption is regarded as a given value,** usually as kWh per kilometre, while proportionality between total power consumption per journey and distance travelled is assumed (Moll, Plötz, Hadwich, and Wietschel 2020; Felipe, Ortuño, Righini, and Tirado 2014). Alternatively, positing a certain *maximum vehicle range*, relative consumption can implicitly be set as a fixed value (Alp, Tan, and Udenio 2019). In either case, consumption is static and not a characteristic of the actual vehicle context (like distance travelled or ambient conditions) (Granada-Echeverri, Cubides, and Bustamante 2020; Wang, Lim, Tseng, and Yang 2018).

(c) **Power consumption is calculated using physical simulation.** This usually involves sophisticated modelling and calculations of the vehicle’s kinetic energy requiring detailed technical parameters but allows to integrate various influencing factors, such as drag, rolling friction to acceleration or brake energy recovery (Lin, Zhou
Imprecise range estimate

Imprecise estimate of variable costs

Tactical planning: fleet management

Operational planning: vehicle dispatch

Imprecise range estimate

Consideration of technically unsuitable vehicles

Consideration of non-cost efficient vehicles

Overambitious electrification

Underachieving electrification

Business risks
- Lack of experience among staff (administrative, drivers, maintenance)
- Unreliable operation: vehicle battery might drain while on route

Decline in profits
- Not all combustion vehicles are substituted by electric trucks although it could reduce costs
- Dispatchers include safety buffers in route planning

Imprecise planning of transport routes

Fig. 8.2 Negative effects of imprecise range estimates on tactical and operational planning
and Wolfson 2016; Goeke and Schneider 2015; Helms, Pehnt, Lambrecht and Liebich 2010).

(d) Total power consumption is calculated using an estimation function that goes beyond a mere proportionality between distance travelled and energy consumed (Liimatainen, van Vliet, and Aplyn 2019; Davis and Figliozzi 2013).

All four approaches require specific input data in order to serve as a data source for electric power consumption. Typically, three different data sources can be distinguished:

(a) **Assumptions**, for example, the assumption that range assured by the manufacturer can be used to derive the vehicle’s relative consumption or that the values from one trial can be used for calculations related to another trial involving the same type of vehicle.

(b) **Standardized values**, for example, values from vehicle surveys as included in the Handbook Emission Factors for Road Transport (HBEFA) (Helms, Pehnt, Lambrecht and Liebich 2010) or derived from standardized driving cycles (Camilleri and Dablanc 2017; Lee, Thomas, and Brown 2013).

(c) **Context-specific real-world values**, i.e. real-world data gathered from the very use case for which consumption data is needed, for example, a case in which data from one electrified package delivery van is taken to plan the delivery round trips of the same van or a different van of the same type operating from the same depot (Taefi, Stütz, and Fink 2017).

It is apparent that either current approaches for range estimation rely on sophisticated simulation models requiring meticulous calibration and precise information about the intended routes, including road gradients, or they require access to precise data from similar use cases as well as the capabilities to process that data. It can be doubted that both are easily available to companies involved in urban logistics, especially since the majority of those companies are small- or medium-sized enterprises, and that the respective requirements can rarely be met on a daily basis (Osypchuk 2019; Oberhofer and Fürst 2013). In practice, companies rely on a planning method assuming a proportionality between range and distance combined with a substantial safety buffer leading to inefficient vehicle use (Stütz et al. 2016).

### 8.3 Towards an Intelligent Method for Range Prediction

To overcome this gap between theoretically applicable estimations based on multiple variables and, hence, inducing substantial effort for data acquisition and the other extreme of range-driving-distance proportionality (Stütz, Fink, Taefi 2018), Fraunhofer IML conceived the research project “EN-WIN”. One objective of this project was to assess the possible increase of range prediction quality when only basic route characteristics (like the number of delivery stops) are considered.
When it comes to data acquisition, it can be safely assumed that this data is definitely available for dispatchers, even in SMEs, as they are elementary results of route planning (Oberhofer and Fürst 2013). Moreover, the project considered ambient temperature as an additional variable and produced a method to collect this data more efficiently (Jerratsch, Herzlieb and Marker 2018). The researchers involved used an extensive trial between 2017 and 2020 to collect data from eight electric trucks of various sizes (4.25 tons to 40 tons) using tracking devices. This article puts the focus on the data collected from the journeys of the 18-ton trucks to address the question whether basic information from vehicle dispatch allows more precise range prediction than just assuming a proportional relationship between energy consumption and travel distance. After data sanitization, a total of 420 days of vehicle operation remained for analysis (cf. Table 8.1).

As a first step, it is safe to assume that a dispatcher has access to the following basic set of information since they directly trace back to transport orders and customers (Seiler 2012):

- Travel distance: length of entire round trip starting and finishing at the depot.
- Number of delivery stops: total number of customers on the delivery route.
- Payload: shipment weight at the beginning of the round trip.

Additionally, using data from public sources, it is also safe to assume that a dispatcher is able to include ambient temperature (at least the average daily temperature recorded at depot location). As a next step, the dominant drivers of energy consumption of these should be included in a range prediction model. With travel distance already considered as a main driver for energy consumption, eight different models each using (a subset of) the aforementioned variables (cf. Table 8.2) could be derived.

A classic least-square model is not sufficient for the present case since it will definitely result in non-zero beta weights for any covariate. Instead, it is desired that the model selects

<table>
<thead>
<tr>
<th>Model no.</th>
<th>Variables used</th>
<th>Ambient temperature</th>
<th>Number of delivery stops</th>
<th>Payload</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>X</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>2</td>
<td>X</td>
<td>X</td>
<td></td>
<td></td>
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<td>X</td>
<td></td>
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<td>X</td>
<td></td>
<td></td>
<td>X</td>
</tr>
<tr>
<td>5</td>
<td>X</td>
<td>X</td>
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<td></td>
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<tr>
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<td>X</td>
<td>X</td>
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<tr>
<td>7</td>
<td>X</td>
<td></td>
<td>X</td>
<td></td>
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<tr>
<td>8</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Table 8.1 Overview of data collected from 18-ton trucks during the course of the “EN-WIN” project</th>
</tr>
</thead>
<tbody>
<tr>
<td>Total days of operation</td>
</tr>
<tr>
<td>420</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Table 8.2 Linear models used for range prediction</th>
</tr>
</thead>
<tbody>
<tr>
<td>Model no.</td>
</tr>
<tr>
<td>-----------</td>
</tr>
<tr>
<td>1</td>
</tr>
<tr>
<td>2</td>
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<tr>
<td>3</td>
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<tr>
<td>4</td>
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<td>5</td>
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<tr>
<td>6</td>
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<tr>
<td>7</td>
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<tr>
<td>8</td>
</tr>
</tbody>
</table>
the best variables to accurately predict energy consumption and range, respectively, while avoiding overfitting. The LASSO (least absolute shrinkage and selection operator) method seemed expedient for that purpose (Tibshirani 1996). Basically, it extends the least-square approach by the concept of penalizing high values for regression coefficients. Since the LASSO may shrink least-square estimators to zero (in contrast to ridge regression), it also performs variable selection and helps us to focus on main drivers of energy consumption (Tibshirani 2011). LASSO is defined as follows:

$$\hat{\beta}_{\text{Lasso}} = \arg\min_{\beta} \left[ y - X\beta \right]^2 + \lambda \sum_{j=1}^{p} |\beta_j|$$

In each of our eight models, y is, of course, energy consumption, while the vector X represents the respective set of explanatory variables (Table 8.2), and β is the vector of regression coefficients. The regularization parameter λ is determined using a tenfold cross-validation. This means our database of 420 days of operation is partitioned into 10 segments of 42 randomly selected days with 9 segments being used to calibrate the model and 1 to test it. The calibration and test procedure is carried out ten times so that each set of 42 days has served exactly once for quality testing. Overall precision of the model is calculated over the ten test runs as an average mean square error over all three iterations.

### 8.4 Results and Discussion

The reported results along with the breadth of the database are detailed in Table 8.3. Prediction quality is provided as a mean absolute percentage error (MAPE) and the goodness of fit as the adjusted coefficient of determination (adjusted $R^2$). Note that the number of records used for each model may deviate due to different availability of input

<table>
<thead>
<tr>
<th>Model no.</th>
<th>Independent variables</th>
<th>Number of records</th>
<th>Adjusted $R^2$</th>
<th>MAPE (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Distance</td>
<td>416</td>
<td>0.801</td>
<td>11.32</td>
</tr>
<tr>
<td>2</td>
<td>Distance, temperature</td>
<td>416</td>
<td>0.869</td>
<td>9.01</td>
</tr>
<tr>
<td>3</td>
<td>Distance, stops</td>
<td>406</td>
<td>0.825</td>
<td>9.35</td>
</tr>
<tr>
<td>4</td>
<td>Distance, payload</td>
<td>60</td>
<td>0.529</td>
<td>18.59</td>
</tr>
<tr>
<td>5</td>
<td>Distance, temperature, stops</td>
<td>406</td>
<td>0.882</td>
<td>7.49</td>
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<tr>
<td>6</td>
<td>Distance, temperature, payload</td>
<td>60</td>
<td>0.532</td>
<td>17.66</td>
</tr>
<tr>
<td>7</td>
<td>Distance, stops, payload</td>
<td>57</td>
<td>0.517</td>
<td>17.71</td>
</tr>
<tr>
<td>8</td>
<td>Distance, temperature, stops, payload</td>
<td>57</td>
<td>0.498</td>
<td>18.63</td>
</tr>
</tbody>
</table>
data. For instance, the lower number of records for models involving payload traces back to the poor reliability of the data recorded by the vehicle-integrated weighing system.

The results suggest that the simple rule of three approach (model 1) can substantially be improved both in terms of model fitness and prediction quality when the model is extended to include ambient temperature and the number of stops (models 2, 3 and 5). Assuming that dispatchers use a safety buffer based on the MAPE when designing round trips, higher precision (lower MAPE) directly translates into more planning flexibility since assumed vehicle range grows. For this purpose, model 5 offers both the highest precision and best model fit. As an unexpected result, including payload (as defined above) as an explanatory variable did not add to the range prediction’s precision. A possible explanation could be that during a delivery route, payload changes with each stop requiring a closer look at the respective stops, their sequence and the change in payload. Mere kinetic considerations make it seem worthwhile to consider other options to integrate payload. Results from model 8 suggest that temperature, after all, could play a minor role compared to the other variables as LASSO eliminates it in this model.

8.5 Conclusion

Predicting energy consumption and, thereby, range for electric trucks are key tasks for fleet managers and dispatchers alike. However, common approaches of range estimation often focus on sophisticated models and methods implicitly assuming continuous availability of different kinds of data. Moreover, it can be expected that, in practice, neither the technical competencies to collect and process data nor the required data to work with those models are available in a company. Therefore, this article illustrated that there is actually a possibility to improve the simple rule of three approach for range estimation by only using data which any logistics planner deals with on a daily basis:

- **Travel distance** which can directly be calculated, even manually, when a dispatcher has decided how to serve the respective customer orders.
- **Number of delivery stops** which is known when the dispatcher has decided which customer orders are allocated to a specific vehicle.
- **Ambient temperature** which can be drawn from public statistics or weather forecasts.

All models discussed are rather simple linear models with few variables, allowing range estimation to be integrated easily into route planning, even in manual procedures. As a first subsequent step, it seems natural to apply similar models to the other vehicle classed from EN-WIN’s field trials.

In model 5, adding only average daily temperature and number of customer stops to the planned travel distance showed promising results, reducing the MAPE to 7.49% from 11.32%. This improvement directly increases route flexibility and reliability of route planning for electric vehicles as observations in the field regularly show substantial safety
buffers with respect to expected range. Given the mere physical importance of gross weight (and, hence, payload) for the kinetic energy involved in transport, it is a surprise to see a decrease in estimation quality when including weight/payload. It has to be considered that the number of datasets with data about vehicle weight is particularly small (57 days, cf. Table 8.3). Models not including payload can make use of about 400 round trips, so it can be assumed that either the mere quantity of records too small or considering the initial payload as a parameter is not expedient since payload lowers or at least changes with each delivery stop (Table 8.3). In this context, it might also be important that no model considered the actual stop sequence and their impact on vehicle payload.

Further research directions are, therefore, targeted at practical methods to increase the number of valid records including payload or gross vehicle weight providing a broader database. Exploring the impact of weight on power consumption is particularly important for urban logistics. Companies able to determine the expected range of a certain vehicle based on actual shipment weights and distances can avoid purchasing vehicles based on exaggerated range expectations which, due to large batteries, may offer a sufficient maximum range but are lacking payload.

When it comes to estimation models, it seems worthwhile to refine the approach and disintegrate each round trip into individual legs for which partial energy consumption is estimated and finally summed up to consumption and maximum range per trip, respectively. This kind of model would allow to consider:

- Stop sequence, i.e. including the actual order size and the respective weight to be unloaded at a specific customer site.
- Trip structure, i.e. the actual distances covered between stops and from or to the depot.

Such kind of approach still requires no further data than currently known to vehicle dispatchers but may (at least for routes with numerous stops) entail a substantial increase in effort to calculate ranges. Possible trade-offs between precision of range estimate and dispatcher’s working hours could, therefore, move into the focus as well.

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