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* *Volvo Trucks, 1 Av. Henri Germain, 69806 Saint-Priest, France: pedro.dias.longhitano@volvo.com*
** Univ. Grenoble Alpes, CNRS, Grenoble INP, GIPSA-lab, 38000 Grenoble*: Christophe.Berenguer@grenoble-inp.fr*
*** *Volvo Trucks, 1 Av. Henri Germain, 69806 Saint-Priest, France: Benjamin.echard.2@volvo.com*

Abstract. The problem of assigning missions to a fleet of electric vehicles has been thoroughly studied in the literature under the name of Electric Vehicle Routing Problem (EVRP), however most versions of such a problem do not take battery degradation into account. One of the main difficulties of battery degradation aware routing is the necessity of including State of Health (SoH) models that are designed for different operation conditions and the necessity of including a realistic State of Charge (SoC) model. In this paper we present a version of the EVRP that includes battery degradation as well as the inclusion of decision variables such as speed and acceleration limitations. We illustrate our approach through numerical experiments.

1. Introduction

Electric mobility has become increasingly important. With this new transport paradigm, it is crucial to account for battery degradation since this component can cost up to 50% of vehicle cost, *Baghdadi* et al (2016), and has also important environmental consequences.

To achieve practical degradation aware routing, it is necessary to describe SoH evolution in the optimization problem, therefore, most of the known battery stress factors must be modeled and related to the performance of missions. As the most important stress factors of batteries are Depth-of-Discharge (DoD) and mean State of Charge (mSoC), *Rosewater (2019*), it is necessary to model the State of Charge (SoC) and connect it to vehicle usage. In most EVRP's, however, SoC models are oversimplified not accounting for the dynamics of the battery and variable terminal voltage, *Pelletier et all (2019)*.

Furthermore, new technologies allow for different decisions to be considered. With today's connectivity, it is possible to change vehicle parameters in order to limit speed or accelerations. Those parameters directly influence usage, impacting battery degradation and enrich the optimization potential.

In this work, we propose and solve an optimization problem that accounts for battery degradation using realistic SoH and SoC models. In this optimization problem, not only route assignment is considered but also vehicle parameters changes, such as maximum speed and acceleration. Therefore, the main contributions of this paper can be summed up as:

- The formalization of an EVRP that accounts for battery degradation, maximum vehicle speed limitation, and maximum vehicle acceleration limitations.
- A SoH estimation method suited for optimization problems that also includes realistic SoC modeling.
- A set of numerical experiments to validate our approach.

Accordingly, Section 2 presents the problem formalization, Section 3 shows the underlying SoH and SoC models, Section 4 presents numerical results and section 5 concludes the paper.

2. Problem Formulation

The goal of this paper is to derive a method to optimally assign missions to a fleet of electric trucks. Missions are seen as points in space, representing clients, that must be visited. Charging stations are also considered so that vehicles can recharge if needed. The mission plan must respect several constraints related to SoC range, vehicle capacity, and other logistical aspects that will be presented later on. All vehicles start at the same point, the headquarters, and must go back to it after finishing the missions.

To formalize this problem, we consider the graph $G = (N,E)$ where nodes N represent every point in space that can be visited by vehicles. $N = C \cup S \cup 0$ where C is the set of clients (missions), S is the set of recharge stations and 0 is the headquarters. E represents the shortest paths between each node. The set of vehicles is denoted by K.

The decision variables of the problem are the following:

- x_{ijz} which is equal 1 if vehicle z performs a displacement from node i to j.
- w_{ijz} which is the payload of vehicle z going from node i to j.
- v_{max_z} which is the maximum allowed speed of vehicle z
- a_{max_z} which is the maximum allowed acceleration of vehicle Z

For the sake of notation, we define $Xz = \{x_{ijz} = 1, \forall i,j \in N\}$ representing the mission plan of vehicle z. We also consider $t_{ij}(v_{max_z},a_{max_z})$, the time necessary to go from node i to j with maximum allowed speeds and accelerations $v_{max_z}$and a_{max_z}, H, the maximum vehicle payload and $SoC(t,X_z,v_{max_z},a_{max_z})$ which is the SoC at instant t of a vehicle following a mission plan X_z with v_{max_z} and a_{max_z}.
The optimization cost C is a combination of degradation, energy and delay costs and can be written as:

$$C = C_{deg} + C_{energy} + C_{delay} \tag{1}$$

The degradation cost is defined as:

$$C_{deg} = \sum_{z\in K} c_{batt}\Delta SoH(X_z,v_{max_z},a_{max_z}) \tag{2}$$

where c_{batt} is a constant proportional to the battery cost and ΔSoH is the variation of SoH caused by following the mission plan X_z with v_{max_z} and a_{max_z}.
The energy cost can be written as:

$$C_{energy} = \sum_{z\in K}\sum_{i\in N}\sum_{j\in C} c_e e_{ijz}(v_{max_z},a_{max_z})x_{ijz} \tag{3}$$

where c_e is a constant representing the price of energy and $e_{ijz}(v_{max_z},a_{max_z})$ is the energy consumed going from node i to j with v_{max_z} and a_{max_z}.
Finally, the delay cost is:

$$C_{delay} = \sum_{z\in K}\sum_{i\in N}\sum_{j\in C} c_d x_{ijz}\max[y_{ijz} - l_j,0] \tag{4}$$

The complete optimization problem can then be written as:

$$\min C \tag{5}$$

subjected to:

$$\sum_{z\in K}\sum_{j\in C} x_{ijz} = 1, \quad \forall i \in N \tag{6}$$

$$\sum_{j\in N} x_{ijz} = 1, \quad \forall z \in K \tag{7}$$

$$\sum_{j\in S} x_{ijz} \leq 1 \quad \forall i \in N,\forall z \in K \tag{8}$$

$$\sum_{z\in K}\sum_{j\in S} x_{ijz} - \sum_{z\in K}\sum_{j\in S} x_{jiz} = 0 \quad \forall i \in N \tag{9}$$

$$\sum_{z\in K}\sum_{j\in S} w_{ijz} - \sum_{z\in K}\sum_{j\in S} w_{jiz} = h_i \quad \forall i \in N \tag{10}$$

$$h_j x_{jiz} \leq w_{ijz} \leq (H - h_j)x_{jiz} \quad \forall i \in N,\forall z \in K \tag{11}$$

$$y_{0jz} \geq t_{0j}(v_{max_z},a_{max_z})x_{0jz} \quad \forall j \in C \cup S,\forall z \in K \tag{12}$$

$$\sum_{z\in K}\sum_{j\in S} y_{ijz} - \sum_{z\in K}\sum_{j\in S} y_{jiz} = t_{ij}(v_{max_z},a_{max_z})x_{jiz} \quad \forall i \in N \tag{13}$$

$$\min SoC(t,X_z,v_{max_z},a_{max_z}) \geq SoC_{crit}, \forall z \in K \tag{14}$$

$$x_{ijz} \in \{0,1\} \tag{15}$$

$$w_{ijz} \geq 0 \tag{16}$$

$$y_{ijz} \geq 0 \tag{17}$$

$$v_{max_z} \in [v^-_{max},v^+_{max}] \tag{18}$$

$$a_{max_z} \in [a^-_{max},a^+_{max}] \tag{19}$$

Inequality (6) imposes that every client is visited once, Constraint (7) guarantees that the number of vehicles used does not exceed the size of the fleet, Constraint (8) limits the number of visits to recharge stations and Constraint (9) imposes that for each incoming arc there is a corresponding outgoing arc. Constraint (10) guarantees that, at each delivery, the payload is reduced according to h_i which is the payload variation at client *i* ($h_i = 0$ if point *i* is the headquarter or a charging station), while Constraint (11) ensures that the maximum payload H is respected and it makes w_{ijz}= 0 when x_{ijz} = 0. Constraints (12) and (13) describe arrival time evolution, ensuring that the displacement duration is respected. Notice that in this formulation, charges are considered to happen instantly as well as deliveries. Constraint (14) imposes the range limitations through SoC.

Constraints (15) through (19) define the proper range of the decision variables. And a^-_{max}, a^+_{max}, v^-_{max}, v^+_{max} are the acceptable limits of a_{max_z} and v_{max_z} respectively.
Additionally, in this model, we consider that anytime a recharge station is visited or a vehicle goes back to the headquarter, it will recharge its battery fully.
The next section presents the models used to compute $\Delta SoH(X_z, v_{max_z}, a_{max_z})$, $e_{ijz}(v_{max_z}, a_{max_z})$ and $SoC(t, X_z, v_{max_z}, a_{max_z})$ based on the decisions variables of the problem.

3. SoH and SoC estimation methods

3.1 *SoH modeling*

To compute the term $\Delta SoH(X_z, v_{max_z}, a_{max_z})$ it is necessary to employ a model that can connect SoH variation to vehicle operation. This requires a degradation model that can be used for application with different usage conditions. We employ the model used by *Xu et al (2016)* in which SoH is expressed as:

$$SoH(t) = e^{-f_d(SoC(t))} \tag{20}$$

with f_d being defined as:

$$f_d(SoC(t)) = \sum_{i=1}^{n(SoC(t))} \omega_i S_\sigma S_\delta S_T \tag{21}$$

where $n(SoC(t))$ is the number of SoC cycles that are obtained through the rainflow-counting algorithm *Downing* et al (1982) of the SoC signal up to time t. S_δ, $S_\sigma$and S_T are stress coefficients related DoD, mSoC and temperature and ω_i is either 1 in a full cycle or 0.5 in a half cycle. The stress factors coefficients are taken from *Xu et al (2016)* and can be expressed as:

$$S_{\sigma_i} = e^{K_\sigma(\sigma_i - \sigma_{ref})} \tag{22}$$

$$S_{\delta_i} = (K_{\delta_1}\delta_i^{\delta_2} + + K_{\delta_3})^{-1} \tag{23}$$

$$S_{T_i} = e^{\frac{K_T(T_i - T_{ref})T_{ref}}{T_i}} \tag{24}$$

where K_σ, K_T, K_{δ_1}, K_{δ_2}, K_{δ_3} are constants estimated through experiments, σ_{ref} and T_{ref} are experimental references. σ_i and δ_i are the cycle amplitude and cycle mean obtained through rainflow-counting and T_i is the mean temperature of the cycle, considered to be normally distributed around the target temperature of the battery management system.
Finally, the SoH variation is expressed as:

$$\Delta SoH(X_z, v_{max_z}, a_{max_z}) = SoH_0 - SoH(X_z, v_{max_z}, a_{max_z}) \tag{25}$$

where SoH_0 is the SoH before following a mission plan and $SoH(X_z, v_{max_z}, a_{max_z})$ is the SoH obtained after performing mission plan X_z with maximum speed and acceleration v_{max_z}, and a_{max_z} respectively

3.2 *SoC modeling*

Since the SoH model relies on the cycle decomposition of SoC(t), it is necessary to estimate SoC while following a mission plan. Most EVRP's that are no concerned with degradation effects approximate SoC to be proportional to the travelled distance or consider SoC variation to be equal to energy consumption *Pelletier et al (2017)*.
To achieve realistic SoH estimation those approximations are limiting, and battery dynamics must be considered. Battery and vehicle dynamics can be combined to obtain SoC by solving the following system of algebraic differential equations:

$$\dot{v} = a(t, X_z, v_{max_z}, a_{max_z}) \tag{26}$$

$$P_{mec}(t) = \frac{\rho_{air}\, C_w\, A\, v(t)^3}{2} + m\, g\, v(t) \sin\alpha + m\, g\, C_r\, v(t) \cos\alpha + m\, a(t) v(t) \tag{27}$$

$$P_{elec}(t) = \frac{P_{mec}(t)}{\eta(v(t), a(t))} \tag{28}$$

$$I(t) = \frac{1}{2R}\left(V_{OC}(SoC(t) - V_I(t) - V_s(t) - \sqrt{(V_{OC}(SoC(t)) - V_I(t) - V_s(t))^2 - 4R_0 P_{elec}(t)}\right) \tag{29}$$

$$\dot{V_s} = -\frac{V_s}{R_s C_s} + \frac{I(t)}{C_s} \tag{30}$$

$$\dot{V_I} = -\frac{V_I}{R_I C_I} + \frac{I(t)}{C_I} \tag{31}$$

$$\dot{SoC} = -\frac{I(t)}{Q_0} \tag{32}$$

Equation (26) is the cinematic relation of vehicle speed $v(t)$ and acceleration $a(t, X_z, v_{max_z}, a_{max_z})$.
Equation (27) expresses the mechanical power as a function of vehicle mass m, gravity acceleration g, road inclination α, C_r is the rolling resistance coefficient and C_w is the drag coefficient and A is the frontal area of the vehicle. Equation (28) expresses the electrical power with $\eta(v(t), a(t))$ being the power train efficiency which is a function of instantaneous speed and acceleration.
Equation (29) to (32) represent the dynamic of the battery that is modeled as a second order circuit. R_I, R_0 and R_s are the resistances of the equivalent circuit, C_I and C_s the capacitances and Q_0 the nominal capacity of the battery.
For the system to be solved, it is necessary to estimate the function $a(t, X_z, v_{max_z}, a_{max_z})$ and the function $Voc(Soc)$. In this work, the acceleration function is estimated using the same method of *Longhitano et al (2022)* and *Basso* et al (2019). It consists of using road information of the path defined by X_z, such as the presence of traffic lights, crossroads and maximum allowed speed, road stretches lengths, and the maximum speed, v_{max_z} and acceleration, a_{max_z}. $Voc(Soc)$ can be obtained empirically or is made available by battery suppliers as a look-up table.
With those equations, the decisions variables of the problem can be used to define the acceleration function and determine the SoC profile which in turns define the variation of SoH. Energy can be computed simply by integrating the electrical power.

4. Results

4.1 *Degradation effect on Routing*

To validate the interest of considering degradation on the optimization model we perform numerical experiments on the synthetic grid shown in Figure 1. In those experiments, first we generate different instances of the problem (a set of random clients, C and random charging stations, S). Each instance is solved three times: once considering $c_{batt} = 0$, which is equivalent to classical EVRP formulations in which only energy consumption is minimized, once considering $c_e = 0$ which is equivalent to minimizing only battery degradation and finally once with $c_{batt} \neq 0$ and $c_e \neq 0$.

Table 1 shows the different routes found solving the optimization problem in the different cases and Figure 1 illustrate the different routes found for instance 1.

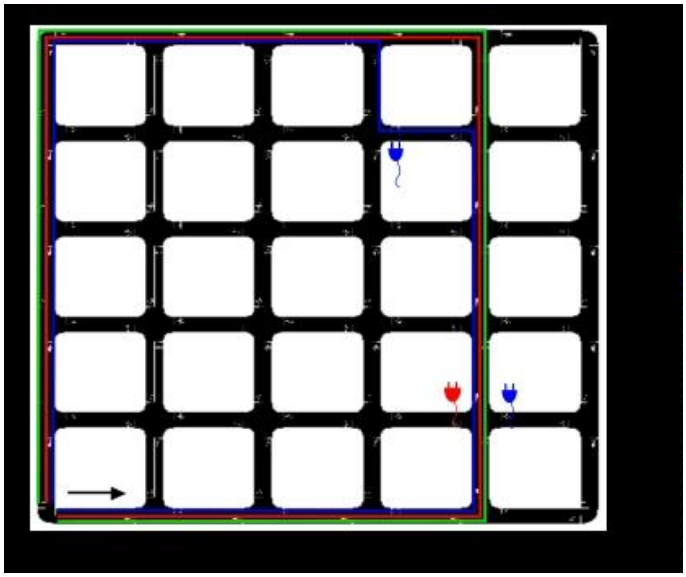
Due to the computational complexity added by the non-linearity of the degradation model and the differential equations of SoC, those instances are solved using genetic programming techniques.

Instance	c_{batt} €	c_e €	**Mission plan**	**Cost C** €
1	10000	0.18	A0, E0, E1*, E3, D5, A4, A2, A0	8.60
1	0	0.18	A0, E0, E3, D5, A4, A2, A0	8.63
1	10000	0	A0, E0, E1*, E3, D4*, D5, A4, A2, A0	8.62
2	10000	0.18	A0, E0, E1*, E3, E5, A4, A2, A0	9.55
2	0	0.18	A0, E0, E3, E5, A4, A2, A0	9.60
2	10000	0	A0, E0, E1, E3, E5, D4*, A4, A2, A0	9.57
3	10000	0.18	A0, B1, C5, F5, F2, D2*, A2, A0	9.56
3	0	0.18	A0, B1, C5, F5, F2, A2, A0	10.52
3	10000	0	A0, B1, C5, F5, F2, D2*, A2, A1*, A0	9.68
4	10000	0.18	A0, B1, B3, D3*, F3, C0, A0	7.65
4	0	0.18	A0, B1, B3, F3, C0, A0	7.73
4	10000	0	A0, B1, B3, D3*, F3, C1*, C0, A0	7.68

Table 1: Solutions of different instances of the problem considering only energy consumption, only battery degradation and both. The symbol * indicates recharging stations.

As can be seen, including battery degradation changes the optimal mission plan. When accounting for degradation, more recharges are added to the plan. They are not necessary from the point of view of ensuring

a minimum SoC level, however they reduce DoD and consequently, degradation. Whenever a vehicle recharges, it stops and needs to accelerate again to leave it, thus spending more energy. Our optimization model can handle this trade-off and find better solutions than the one found by considering only energy consumption



or only battery degradation.

Figure 2 shows the SoC trajectories of the different solutions for instance 1. It shows that the extra charges indeed reduce SoC amplitude and even if they introduce extra cycles, since their amplitude is smaller, they create less damage.

Figure 1. Routes found for instance 1. The red route indicates the solution when accounting for degradation and energy consumption (Case A). The green route indicates the solution of the classic EVRP version where only energy is considered. The blue route is the solution considering only degradation.

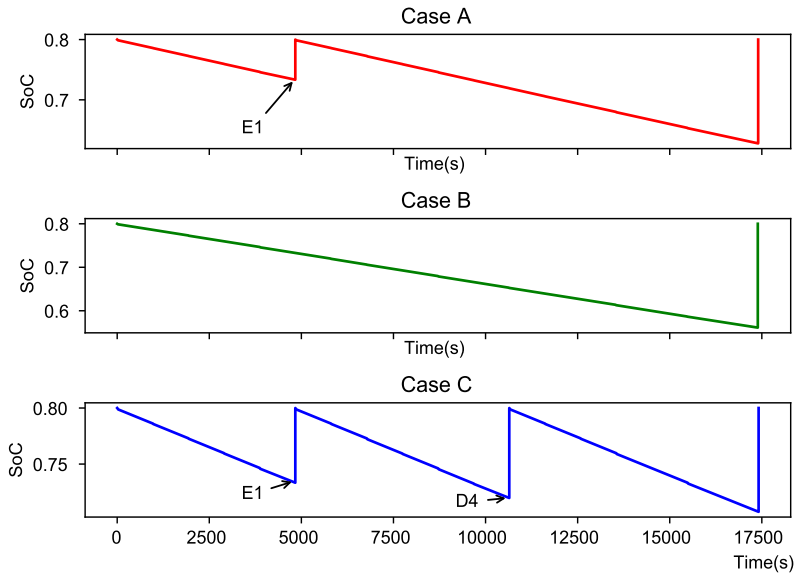


Figure 2. SoC trajectories for different routes found for instance 1.

Accounting for degradation leads to cost improvement in all instances. It is important to highlight that even in instances where the cost reduction is subtle, since SoH evolves slowly, small reductions in degradation add up through time and can lead to several extra months of operations.

4.2 *Speed and acceleration effect*

To isolate the effect of the parameters v_{max_z} and a_{max_z} a second set of experiments is performed. Instances of the problem are generated randomly. Each instance is solved twice, once with v_{max_z} and a_{max_z} as decision variables and once with them set as v^+_{max} and a^+_{max}. Results are shown in Table 2.

Number of clients	**Number of charging stations**	**Cost C (*not acting* on speed and acceleration)**	**Cost C (*acting* on speed and acceleration)**
5	7	6.90	6.39
5	8	7.20	6.74
10	10	11.3	10.6
5	10	6.83	6.27
3	7	4.83	4.36

Table 2: Solutions of different instances of the problem considering the possibility of affecting maximum vehicle speed and acceleration.

As can be seen, limiting speeds and accelerations has a positive impact on the overall cost. This is a direct consequence of equation 27. The cost reduction is a reflex of less energy consumption but also less degradation, since SoC cycles will have smaller amplitudes because of affecting such parameters.

5. Conclusion

This paper presented a variation of the EVRP that accounts for degradation and limitation on speeds and accelerations. To make it useful for degradation minimization in realistic scenarios, the optimization model is built upon a realistic SoC estimation method. Since both the degradation and SoC models are computationally challenging to incorporate in optimization problems, a genetic algorithm was used to solve it. Through numerical experiments, the importance of realistic SoC modeling, degradation-aware decision-making and limiting speeds and accelerations is shown. Incorporating degradation and extending the set of possible actions of the problem yields to better solutions than the most usual optimization models. In real life applications, this can have a beneficial impact since it can extend the useful life of vehicles and reduce the long-term exploitation cost.

In future works, it is necessary to compare the proposed model with real vehicle data, both for SoC and SOH calibration. Incorporating stochastic elements is also desirable. For example, traffic randomness can highly affect energy consumption and delays and must, therefore, be accounted for. Long-term routing methods are also interesting paths for future research.

From an algorithmic point of view, developing new optimization techniques for this problem is also an interesting research path since genetic algorithms do not necessarily converge to a global minimum and due to the computational complexity, performance is still a limiting factor for solving bigger instances.

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