An Approach to Prognosis-Decision-Making for Route Calculation of an Electric Vehicle Considering Stochastic Traffic Information

Heraldo Rozas[1], Diego Muñoz-Carpintero[2], Aramis Perez,[3], Kamal Medjaher[4] and Marcos Orchard[5]

[1,2,3,5] *Department of Electrical Engineering, University of Chile, Santiago, 8370451, Chile*
{heraldo.rozas, dimunoz, aramis.perez, morchard} @ing.uchile.cl
[4] *Production Engineering Laboratory (LGP), INP-ENIT 47 Av. dAzereix, 65000 Tarbes, France*
kamal.medjaher@enit.fr

Abstract

We present a Prognosis-Decision-Making (PDM) methodology to calculate the best route for an Electric Vehicle (EV) in a street network when incorporating stochastic traffic information. To achieve this objective, we formulate an optimization problem that aims at minimizing the expectation of an objective function that incorporates information about the time and energy spent to complete the route. The proposed method uses standard path optimization algorithms to generate a set of initial candidates for the solution of this routing problem. We evaluate all possible paths by incorporating information about the traffic, elevation and distance profiles, as well as the battery State-of-Charge (SOC), in a prognostic algorithm that computes the SOC at the end of the route. In this regard, the solution of the optimization problem provides a balance between time an energy consumption in the EV. The method is verified in simulation using an artificial street network.

1. Introduction

The main goal of Prognosis-Decision-Making (PDM) is to provide a framework capable of supporting the decision-making process using information obtained from prognosis algorithms (Balaban & Alonso, 2013). While most of the PHM community efforts have been concentrated in the diagnosis and fault prognosis topics, contributing to an abundant literature, there is still little work on the PDM domain. A good example to illustrate this situation is the case of Li-ion batteries in EVs, where the number of articles dedicated to the problem of State-of-Charge (SOC) estimation and prognosis is considerable (Zou, Hu, Ma, & Li, 2015; Duong et al., 2015; Sun, Xiong, & He, 2016; Hu, Jiang, Cao, & Egardt, 2016). However, works dealing with the inclusion of the information obtained from these algorithms for PDM with a PHM perspective is scarce. Something similar occurs with the estimation of the State-of-Health (SOH) of batteries and the inclusion of this information in the solution of routing problem of EVs.

The EVs are entering into market as good alternatives to reduce the pollution of the environment. Many governments consider the use of battery-powered EVs as important factors to fulfill their environmental goals because the absence of exhaust emissions can contribute to reduce local air pollution (Jensen & Mabit, 2017). The incorporation of electric transportation technology is an emerging challenge for the transportation sector, and also a major opportunity for logistics operations from an environmental and cost perspectives (Arslan, Yıldız, & Karaşan, 2015). In this sense, solving the routing problem for EVs in the city is an important task as it will allow an efficient operation of EVs. However, solving the routing problem is not a easy task due to the existence of at least two sources of uncertainty: stochastic traffic and SOC estimation.

This article proposes a methodology for finding the best route of an EV to reach a destination. A set of feasible routes to reach the destination are evaluated using a prognosis algorithm. After this evaluation, the algorithm will choose the route that minimizes the total travel cost. Simulation results show that there are benefits to calculate the route of an EVs by incorporating prognosis techniques. More precisely, they show that the intuitive shortest path solution of the routing problem can be improved by adding the resulting information from prognosis to choose the optimal path.

This paper is organized as follows. Section 2 presents a brief literature review of PDM and routing of EVs. Section 3 introduces the proposed methodology for finding the optimal route of an EV. Finally Section 4 presents simulation results and concluding remarks are drawn in Section 5.

2. BRIEF LITERATURE REVIEW

2.1. PDM

Few PDM developments have been done in a PHM context. This section presents a summary and discussion on the few that were developed for aeronautical and terrestrial vehicles applications.

PDM has been developed and used for aeronautical applications in (Balaban & Alonso, 2012, 2013). A methodology for the implementation of a PDM scheme is proposed in (Balaban & Alonso, 2012). Here the decision-making problem is formulated and presents a solution method for the optimization problem. The work of (Balaban & Alonso, 2013) extends the previous methodology to deal with the problem of finding the route of an unmanned aerial vehicle (UAV). The basic idea is to maximize the economic benefit by traveling to waypoint locations with the greater reward values, considering that the UAV has to return to the initial point and that the energy is bounded within adequate ranges.

In (Balaban et al., 2013) and (Sweet et al., 2014) the authors study PDM in the context of terrestrial vehicles, precisely a K11 Planetary Rover Prototype. The PDM approach is studied using a simulator in (Balaban et al., 2013). A physical model of the rover is developed and the optimization problem is formulated to find the visits to the waypoints considering restrictions on the battery and the SOH of the system. A physical implementation of the work presented by (Balaban et al., 2013) is then developed and presented in (Sweet et al., 2014). The main focus of this work is to design and implement the required hardware to validate the PDM methodology on the rover. Results showed that the rover was capable of following the optimized route considering the defined restrictions.

2.2. Routing of EV

As stated by (Brandstätter et al., 2016), it is possible to use several criteria to find the optimal routes from point A to point B, while respecting the battery voltage limits (lower and upper bounds) of plug-in battery electric vehicles (PBEVs).

Among them, the following objectives might be relevant:

- Minimize energy consumption.
- Minimize travel time.
- Minimize total costs such as: traveling, charging, drivers, to mention a few.

A thorough revision of the literature of EVs routing problems can be found on (Pelletier, Jabali, & Laporte, 2016). Many works have focused on the optimal routing problem of EVs, for instance (Arslan, Yldz, & Karaan, 2015; Barco, Guerra, Muñoz, & Quijano, 2017; Shao, Guan, Ran, He, & Bi, 2017). However, these efforts approach the problem from a transportation or operations research perspective, and these perspectives lack of a PHM-related focus. Particularly, factors such as uncertainty on the SOC estimations, SOH models and their impact on the route calculation, changes on the internal impedance or maximum power indicators are not considered, or in case they are considered they are accounted separately. Furthermore, in (Pelletier, Jabali, Laporte, & Veneroni, 2017) the authors highlight the relevance and need of the SOH of batteries and its inclusion on decision-making problems related to EVs.

3. DESCRIPTION OF THE PROPOSAL

In this section we will describe the main aspects of the proposed methodology for the routing of EVs. This is briefly described here, while a deeper presentation is made the following sub sections.

The key factors to address in routing problems are the cost of travel (CT) and the travel time (TT). The minimization of these two quantities are the most common requirements in the vehicle routing context (Brandstätter et al., 2016). A simple model of the systems is used to estimate both the CT and the TT. In this case, the CT can be calculated as the required energy to complete the route. Particularly, in the case of EVs this quantity is equal to the difference between the final and initial SOC (we will not consider battery charging during transit).

The goal of the proposed method is to find the optimal route of a single EV in a street network to travel from the Starting-Point (SP) to the End-Point (EP). Since the method of transportation is an EV, the following factors regarding the possible routes are taken into account:

- Stochastic traffic information.
- Elevation profiles.
- Distance.

As mentioned previously, finding a solution to this routing problem is not an easy task since two uncertainty sources are present: traffic information and the SOC of the Li-ion battery that energizes the EV.

In our approach the street network is modeled as a directed graph. The optimal path is chosen at the SP, taking into a consideration the current state of traffic and the current SOC estimation. Therefore, when the EV is at the SP, the proposed methodology executes the following procedure. First, it calculates the K shortest paths (in terms of physical length of the routes, i.e. the distance from SP to EP along the path), with the K-Shortest Path algorithm, between the SP (also referred as the current node) and the EP. Second, for each of these K paths, a prognosis algorithm is executed to characterize them probabilistically in terms of TT and the final SOC. Finally, the optimal path is chosen according to the evaluation of a cost function. This procedure is shown in Figure 1.

For the purpose of this research effort, we will assume that the EV corresponds to a Nissan Leaf. Its characteristics, electric and mechanical model are presented in (Espinoza, Pérez, Orchard, Navarrete, & Pola, 2017). The following subsections will present in more detail the proposed methodology.

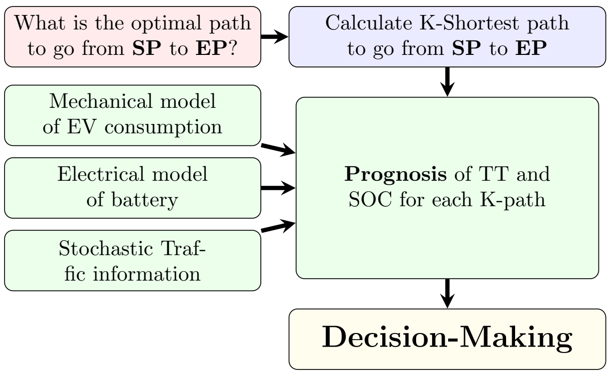


Figure 1. Graphic abstract of the proposal

3.1. Street networks and traffic information model

The street network is modeled as a directed graph or digraph. It consists of an ordered pair $G = (V, E)$, where V is a finite set of nodes or vertices and E is a finite list of edges. Each street corner is represented as a node. Therefore, $\forall a, b \in V$, $(a, b) \in E$ if there exists a street with direction $a \rightarrow b$ and there is no other node in between.

The goal is to choose the optimal route to go from one point of the city to another. Here, we will consider paths only from one node to another. Given the above, we define a path. It is defined as a sequence of nodes $(v_0, \cdots, v_n)$, where $(v_{k-1}, v_k) \in E, \forall k = 1, \cdots, n$. Two nodes a and b of a graph G are called connected if there exists a path with a starting node a and finishing node b. If all pairs of nodes of G are connected, G is called connected (Jungnickel, 2013). We only work with connected graphs. For our simulation study, the street network model can be seen Figure 2a, where $|V| = 121$. At this first proposal, where the main objective is to illustrate the methodology, a simplified street network and traffic model are assumed. These will be improved in the future for closer to reality testing of the methodology.

As mentioned, our streets network model takes into account the distance, inclination and stochastic traffic information between two nodes. Each node has a coordinate $\vec{X} = (x, y, z)$ in a 3D model as shown in Figure 2b, therefore, the distance and the inclination are defined as the following functions:

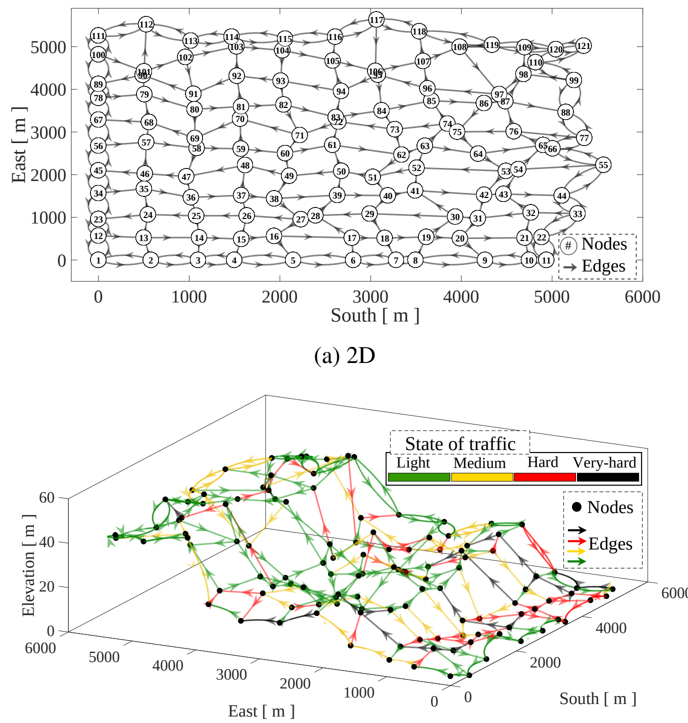
- Distance: $d : E \mapsto \mathbb{R}^+$

$$d(a, b) = \left\| \vec{X}_a - \vec{X}_b \right\| \tag{1}$$

- Inclination: $\phi : E \mapsto (-\frac{\pi}{2}, \frac{\pi}{2})$

$$\phi(a, b) = acos\left(\frac{|x_a - x_b|}{d(a, b)}\right) \tag{2}$$

The stochastic traffic information is incorporated by the velocity of the street; we have assumed that the driver cannot choose the driving speed and it is a random variable. Particularly, we assume that the velocity of each edge depends the traffic state, which distributes as a normal function as shown in Table 1. Thus, for a certain hour we may have a street networks as is shown Figure 2b, where the color of edge indicates its state of traffic (speed in the edge).



(a) 2D

(b) 3D

Figure 2. Street networks and state of traffic model. The head of the arrows indicates the direction of the street and its color is the current state of traffic.

Status of traffic	μ	σ	Color
Light	60	5	
Medium	50	5	
Hard	40	5	
Very Hard	30	5	

Table 1. Conditional distribution of streets velocity given the state of traffic.

3.2. Mechanical model of the EV

The energy needed for the propulsion of EV can be calculated by Newton's second law (Garcia-Valle & Lopes, 2012):

$$M \cdot \ddot{z} = F_T - F_R \tag{3}$$

where M is the overall mass of the EV, $\ddot{z}$ is the EV acceleration, F_T is the total traction force and F_R is the total resistive force.

F_R can be decomposed as the sum of several forces: gravity (f_1), aerodynamic (f_2) and drag (both static (f_3) and dynamical (f_4)). Considering the above we can obtain an expression for each resistive force:

$$f_1(\theta, \dot{z}) = M \cdot g \cdot sin(\theta) \tag{4}$$
$$f_2(\theta, \dot{z}) = 0.5 \cdot C_d \cdot \rho_a \cdot A \cdot (\dot{z} + u_w)^2 \tag{5}$$
$$f_3(\theta, \dot{z}) = g \cdot cos(\theta) \cdot c_{r1} \tag{6}$$
$$f_4(\theta, \dot{z}) = g \cdot cos(\theta) \cdot c_{r2} \cdot \dot{z} \tag{7}$$

where g is the gravitational constant of acceleration equal to $9.8(m/s^2)$, $\theta(rad)$ is the angle of inclination of the street, $u_w(m/s)$ is the velocity of the wind and the other parameters are proper of the EV and they are shown in the Table 2. These parameters are extracted from (Espinoza et al., 2017).

Parameter	Value	Description
M	1525	EV + driver mass (kg)
C_d	0.29	Drag coefficient (dimensionless)
A	2.27	Surface frontal area (m^2)
C_{r1}	0.01	Static drag coeff. (dimensionless)
C_{r2}	1.789e-4	Dynamic drag coefficient (s/m)

Table 2. Parameters of EV

Finally, from (3)-(7), it is possible to calculate the traction power as follows:

$$P_T(\theta, \dot{z}) = F_T(\theta, \dot{z}) \cdot \dot{z} = \dot{z} \left(M \cdot \ddot{z} + \sum_{i=1}^{4} f_i(\theta, \dot{z}) \right) \tag{8}$$

It is relevant to note that in our street networks model (see subsection 3.1) for every edge (a, b), its inclination and distance are constant, and while the velocity is a random variable it is assumed constant along the edge once it is sampled. Therefore, given a sample of the velocity in edge $\dot{z}(a, b)$, the power is constant along the edge and is defined as follows:

$$P_T(a, b) := P_T\left(\theta(a, b), \dot{z}(a, b)\right) \tag{9}$$

In addition, we can calculate and define the TT to go from a to b as follows:

$$TT(a, b) := \frac{d(a, b)}{\dot{z}(a, b)} \tag{10}$$

Then, from (9)-(10) we can calculate and define the energy consumption to go from a to b as follows:

$$E_T(a, b) := P_T(a, b) \cdot TT(a, b) \tag{11}$$

3.3. Electrical model of the Li-ion battery

The electrical model of the Li-ion battery is based on the work presented in (Pola et al., 2015) except that we have assumed that the state related to internal resistance is constant. Taking this into consideration, the resulting state-space model to estimate the SOC can be described by the following equations:

- State transition model:

$$\begin{aligned} SOC(k+1) = SOC(k) - E_c^{-1} \cdot \Delta T \cdots \\ \cdot (I(k)^2 \cdot R_{in} + y(k) \cdot I(k)) \end{aligned} \tag{12}$$

- Measurement equation:

$$y_k = V_{oc}(SOC(k)) - I(k) \cdot R_{in} \tag{13}$$

where $I(k)$ is the discharge current, $y(k)$ is the measured voltage, ΔT is the sample time, R_{in} is the internal resistance and E_c is is the expected total energy delivered by the battery. Particularly, in our case $E_c = 76098121$ [J], since the battery parameters used in (Espinoza et al., 2017) are considered.

3.4. Dynamic model for prognosis of travel time and state of charge

Given a certain path $(v_0, \cdots, v_n)$, we are interested in characterizing its performance. In this case, the variables that will determine the performance of the path are the energy consumption and the time it takes to go through it. More precisely, we want to estimate the TT and state of charge SOC of the battery at the EP. For this, it is necessary to take into account factors like driving velocity, inclination and distance.

To find the TT and SOC at the EP, using the information known at the SP, we need to find the evolution of these variables. Then we need a dynamic model. We propose a dynamic model that is discretized by the nodes of the path. Thus, $x(k)$ denotes the current state x when the EV is in node v_k.

We define the following variables

- $t(k) := TT(v_k, v_{k+1})$, with $TT(\cdot, \cdot)$ as defined (10).

- $E(k) := E_T(v_k, v_{k+1})$, with $E_T(\cdot,\cdot)$ as defined in (11).

Note that the EV has a velocity that is defined by the edge $(k, k+1)$ where it is at the moment. Since the variables $t(k)$ and $E(k)$ are a function of the velocity, which is defined by the edge, the sequence of variables $t(k)$ and $E(k)$ is defined by the sequence of edges of each path. Since traffic is a random variable with a given distribution, the sequences of $t(k)$ and $E(k)$ are not deterministic and have a distribution for each path.

Now, the dynamic equation for the evolution of TT is:

$$x_1(k+1) = x_1(k) + t(k) \tag{14}$$

where $x_1(k)$ is the accumulated travel time to node v_k. Basically, it states that the accumulated TT at node v_{k+1} is equal to accumulated TT in v_k plus the TT between v_k and v_{k+1}.

The second equation models the SOC as follows:

$$x_2(k+1) = x_2(k) - \frac{E(k)}{E_c \cdot \eta} \tag{15}$$

This equation is based on (12), but energy consumption is calculated in a different manner for each step. While the energy consumption is modeled by electrical principles in (12), here it is modeled in a mechanical manner by introducing an efficiency conversion rate: η.

The state transition model for travel time and state of charge that will be used for prognosis is then given by (14) and (15) and has $t(k)$ and $E(k)$ as inputs. Clearly the evolution of x_1 and x_2 is not deterministic due to the uncertainty related to the SOC at the SP and the street velocity along each edge, which results in uncertain values of $t(k)$ and $E(k)$.

3.5. Cost function

A performance metric is needed to evaluate the quality of the different paths. We have proposed the following expression to quantify the total cost of a certain path between the SP to the EP:

$$J(path) = \lambda \cdot x_1(EP) - (1-\lambda) \cdot x_2(EP) \tag{16}$$

where $\lambda > 0$ is a tuning parameter. The goal is to minimize (16). This way, if we are interested in only minimizing TT, then λ is set to 1. However, if $\lambda < 1$, then a penalty is applied to small values of the SOC indicating a preference for large SOCs.

3.6. Prognosis-based Particle-Filter (PPF)

Event prognosis schemes intend to characterize future operational risk based on long-term predictions for the evolution of a set of fault indicators. In the case of PPF (Orchard & Vachtsevanos, 2009), the main concept is to model the propagation of uncertainty in time based on a stochastic state-space model of the faulty system, a probabilistic characterization of future operating profiles, and a particle-filter-based estimate of the state probability density function (PDF). Thus, it is assumed that the system state is being continuously estimated according to Particle-Filter (PF) methodology (Arulampalam, Maskell, Gordon, & Clapp, 2002), and the future PDF's are described by a set of weighted-particles.

The PF is a Bayesian processor and its main goal is to sequentially approximate the posterior PDF of the state by a set of weighted particles. Thus, at time k the estimate of the posterior PDF of x is given by:

$$p(x(k)|y(1), \cdots, y(k)) = \sum_{i=1}^{N_p} w_i(k)\delta(x(k) - x^i(k)) \tag{17}$$

where $\{x_i(k), w_i(k)\}_{i=1}^{N_p}$ is a set of weighted-particles, N_p is the number of particles, $x_i(k)$ is position of particle i and $w_i(k)$ is the weight of particle i, and $\delta(x) = 1$ if $x = 0$ and $\delta(x) = 0$ otherwise. The estimation process has two stages: prediction and update.

In the prediction stage, each particle is propagated one time ahead:

$$x^i(k+1) \sim q(x(k+1)|x^i(k)) \tag{18}$$

where $q(x(k+1)|x^i(k-1))$ is the conditional distribution of the states at time $k+1$ given the state at time k, and is calculated using the state transition equations.

In the update stage, a new measurement arrives and is employed to update the weight of each particles:

$$w_i(k+1) \propto w_i(k) \cdot p(y(k+1)|x^i(k+1)). \tag{19}$$

where $p(y(k+1)|x^i(k+1))$ is the likelihood, it is calculated using the equation of observation. Finally, the weights are normalized.

A graphic summary of the PF is shown in Figure 3. This procedure, as presented above, is the simplest PF implementation. This and other implementations are exposed in depth in (Arulampalam et al., 2002).

The PPF algorithm presented in (Orchard & Vachtsevanos, 2009) uses the PF, but for a different goal, and thus has some substantial differences. The PF is employed for prognosis purpose, therefore there are not measurements and the update step can not be applied. To treat this problem the authors propose a new methodology, as shown next.

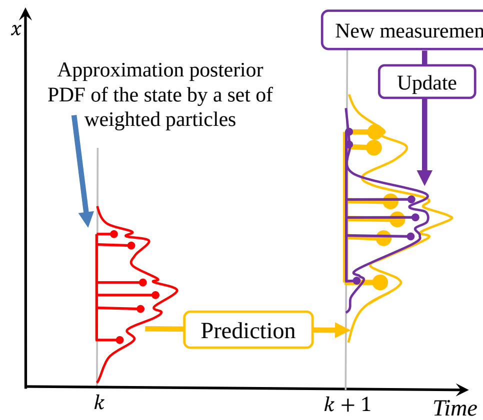


Figure 3. Example of estimate posterior pdf of the state obtained from PF. The prediction and update stages are graphically shown.

The prognosis executed at time k starts with a set of N_p weighted-particles $\{x_i(k), w_i(k)\}_{i=1}^{N_p}$. Then, the particles are propagated step by step according to the state transition equation. In general, to estimate the state PDF at time $k+\tau$, for $\tau \in \{1, ..., n\}$, we need to propagate the particles from $k+\tau-1$ to $k+\tau$. To calculate the PDF of the one-step propagated particles conditional to the previous state, we apply the law of total probabilities:

$$p\left(\hat{x}(k+\tau)|\hat{x}(k+\tau-1)\right) \approx \sum_{i=1}^{N_p} w_i(k+\tau-1) \cdot \hat{p}\left(x_i(k+\tau)|\hat{x}_i(k+\tau-1)\right). \quad (20)$$

Note that $\hat{p}\left(\hat{x}_i(k+\tau)|\hat{x}_i(k+\tau-1)\right)$ is related to the state transition equations thus a characterization of the futures inputs of the system is necessary. An update of the particle weights is also necessary, but as mentioned earlier, this cannot depend on the availability of new measurements in future time instants because they are unknown. One approach to circumvent this issue, and that has proven particularly useful in large prediction horizons (Orchard & Vachtsevanos, 2009), is based on the regularized PF algorithm (Musso, Oudjane, & Le Gland, 2001). Instead of updating particle weights in each prediction step, the uncertainty is represented by a resampling of the predicted state.

3.7. Prognosis-based Decision-Making

The actual step-by-step methodology for finding the best path is defined here. The first step is to calculate the K shortest paths, in terms of physical distance (see model of distance in Eq. 1), from the SP to the EP. For this purpose we employ the K-Shortest Path algorithm presented in (Yen, 1971). Then, for each of the K paths, a prognosis algorithm is run. The prognosis is implemented using the PPF as proposed by (Orchard & Vachtsevanos, 2009) (and described in Section 3.6), and considering the state-space equations of (14) and (15). For prognosis purposes, a characterization of the future profile of the TT and SOC of the EVs at the EP is needed. This is generated by sampling from the probability distribution of the velocity for each edge. With this information it is possible to calculate the energy consumption, and after several realizations the prognosis can be performed. Though the the most precise method for this purpose is Monte Carlo (MC) simulation, we will use PPF as presented above. It is a functional approximation of MC for online prognosis purposes, which has reduced computational costs with similar performance.

Although a common goal in prognosis is to perform predictions of the Remaining Useful Life (RUL) and End of Life (EOL), here the prognosis method is implemented according to the perspective described in (Balaban & Alonso, 2012); the prognosis method aims to characterize the evolution of the plant state through time; e.g., due to wear or degradation (in our case SOC).

Finally, the decision is made considering the expected value of the functional of costs. In other words, the optimal path $path^*$ is chosen as the one of the K shortest paths that yields the minimum expected value of the cost J:

$$path^* = \arg\min \left\{\mathbb{E}_{\hat{x}}(J(path_i)) : \; i = 1, \ldots, K\right\} \quad (21)$$

The methodology presented here consists in general terms on (see Figure 1): the generation of the K shortest routes, their posterior evaluation by means of the PPF and finally the selection of a route with (21). However, in each step different methods (or cost function) may be used depending on user requirements (for instance deterministic formulation or Robust Optimization) or the potential situation that further research indicates that there are better methods to use at a certain step.

4. RESULTS

In order to evaluate the proposed method we consider the street network from Figure2, and we study the results obtained when finding the route from node 10 to node 116. The resulting TT and CT obtained with the proposed method are compared to those obtained by assigning the shortest path found by Dijkstra's algorithm because this route should be the optimal when the SOC of the batteries and the traffic uncertainty are ignored. Dijkstra's algorithm finds the shortest path route, thus the solution of the K-Shortest Path algorithm with $K = 1$ is equivalent to that of Dijkstra's algorithm. For the simulations it is assumed that the traffic conditions remain constant during the transit of the vehicle. Though this assumption may be unrealistic since traffic is dynamic, the setting is good enough to evaluate the route selection methodology. The simulations were performed on a desktop computer,

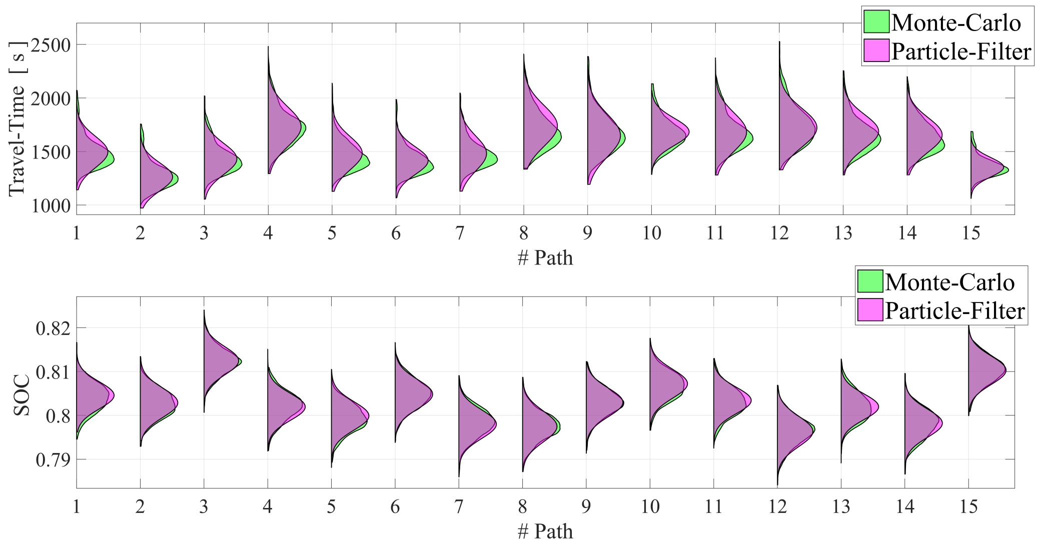


Figure 4. Results of prognosis: PDF of the states at the EP of each path obtained by the K-shortest path algorithm. The different paths are ordered in the horizontal-axis from shortest to longest distance from the SP to the EP, i.e. path i is the ith longest-distance path as found by the K-shortest path algorithm.

Case	Mean	Std	Min	Max
Shortest-Path	1492.179	144.322	1202.889	2079.665
Proposed Method	1282.718	130.485	1052.863	1748.633

(a) Cost considering $\lambda = 0$. Optimal-Path= 2

Case	Mean	Std	Min	Max
Shortest-Path	0.804	0.003	0.795	0.817
Proposed Method	0.812	0.003	0.801	0.824

(b) Cost considering $\lambda = 1$. Optimal-Path= 3

Case	Mean	Std	Min	Max
Shortest-Path	-0.094	0.069	-0.244	0.196
Proposed Method	-0.191	0.057	-0.320	-0.001

(c) Cost considering $\lambda = 0.0004$. Optimal-Path= 15

Table 3. Decision-making outputs with different purposes.

with an Intel i5 $3(Ghz)$ processor and $8(GB)$ of RAM.

For the proposed routing method, the TT and CT of the $K = 15$ shortest paths are characterized using the traffic and inclination information with the PPF as described in Section 3.7. The execution time of the task of finding these paths with the K-Shortest Path algorithm was $1.8(s)$. The estimated distributions of the TT and CT (in the form of SOC) at the end of the K routes obtained with the PPF (implemented with 400 particles) are shown in Figure 4. Here we also include those that are obtained with the MC prognosis (implemented with 10000 replications) in order to validate that the PPF results are satisfactory. While the MC is the most precise method, the simplification of the PPF reduced the simulation time from 3.4 (s) with MC to 1.2 (s), and as can be seen in 4 the results are similar. This justifies the use of particle-filtering as a good technique to calculate the PDFs in a much quicker way with a similar performance.

Three different optimization scenarios are considered to evaluate the performance of each route. In the first one, $\lambda = 1$. This means that the user is interested in just minimizing the TT. For the second scenario $\lambda = 0$, so that the TT is not considered, and the optimization only seeks the maximization of the SOC at the end of the trip. Finally, for the third scenario $\lambda = 0.004$, which is set to seek a balance between the TT and SOC. Note that while this seems a near zero value, meaning mainly a SOC optimization, it is appropriate for finding a balance given the scales of the TT and SOC values. The results of each scenario are presented in Table 3.

On the first scenario, which consists on minimizing the TT (see Table 3a), it can be noted that on average the user can reduce up to 210 (s) (corresponding to a 14% improvement) if Route 2 is selected instead of the shortest one; a similar analysis can be performed using the minimum and the maximum. In general, Route 2 has a better performance than Route 1 (which is the shortest path).

For the second scenario (SOC maximization, see Table 3b), Route 3 is selected and it allows to save on average up to 1% of the SOC, a considerable value if accounting that the full autonomy of the EV is greater than 100 [Km], which means that the extra 1 [Km] can be used otherwise.

Finally, for the third scenario (see Table 3a) the proposed methodology chooses path number 15. It allows to save on average up to 0.6% of the SOC and to reduce on average a 12% of the TT. This demonstrates that is possible to choose a route that provides a good balance between TT and SOC accomplishing both purposes.

Overall, it is shown that the PDM methodology can improve the results obtained with the shortest path algorithm.

5. CONCLUSION

In this work we have proposed a PDM methodology for finding the optimal route of an EV from an starting to a ending node in a street network. A PPF, commonly used in the PHM community, is used to estimate the performances of candidate routes. Since the PPF allows to propagate the uncertainty about the future evolution, it is suitable to incorporate stochastic traffic and SOC to the routing problem. The results show that the intuitive shortest path can be improved by the PDM framework.

Future research will focus on studying the PDM based EV routing problem under a more realistic setting, performing simulations on a real street network and with real traffic data. Along the same line, we will also explore making the models more realistic by incorporating new parameters of interest to the routing methodology, such as the variable internal impedance, the state of maximum power and the SOH of batteries. We will also study the closed-loop application of this strategy, such that the routes can be re-computed at different stages before reaching destination, so that the routes can be changed in the event of unexpected changes in traffic or the battery state. We will study the use of different methods in the different steps of the methodology, and ultimately, we will aim to extend this methodology to be applied for online routing of EVs for taxi services.

ACKNOWLEDGMENT

This work has been partially supported by FONDECYT Chile Grant No. 1170044, the Advanced Center for Electrical and Electronic Engineering, AC3E, Basal Project FB0008, CONICYT, and project CONICYT - FONDECYT Postdoctorado - 3170040. Also, the authors want to thank project CONICYT PIA ACT1405. The work of H.R was supported by CONICYT-PFCHA/Magister Nacional/2018-22180232.

REFERENCES

Arslan, O., Yıldız, B., & Karaşan, O. E. (2015). Minimum cost path problem for plug-in hybrid electric vehicles. *Transportation Research Part E: Logistics and Transportation Review*, *80*, 123–141.

Arslan, O., Yldz, B., & Karaan, O. E. (2015). Minimum cost path problem for plug-in hybrid electric vehicles. *Transportation Research Part E: Logistics and Transportation Review*, *80*, 123 - 141. doi: https://doi.org/10.1016/j.tre.2015.05.011

Arulampalam, M. S., Maskell, S., Gordon, N., & Clapp, T. (2002). A tutorial on particle filters for online nonlinear/non-gaussian bayesian tracking. *IEEE Transactions on signal processing*, *50*(2), 174–188.

Balaban, E., & Alonso, J. J. (2012). *An approach to prognostic decision making in the aerospace domain* (Tech. Rep.). National Aeronautics and Space Administration Moffett Field Ca Ames Research Center.

Balaban, E., & Alonso, J. J. (2013). A modeling framework for prognostic decision making and its application to uav mission planning. In *Annual conference of the prognostics and health management society* (pp. 1–12).

Balaban, E., Narasimhan, S., Daigle, M., Roychoudhury, I., Sweet, A., Bond, C., & Gorospe, G. (2013). Development of a mobile robot test platform and methods for validation of prognostics-enabled decision making algorithms. *International Journal of Prognostics and Health Management*, *4*(1), 87.

Barco, J., Guerra, A., Muñoz, L., & Quijano, N. (2017). Optimal routing and scheduling of charge for electric vehicles: A case study. *Mathematical Problems in Engineering*, *2017*.

Brandstätter, G., Gambella, C., Leitner, M., Malaguti, E., Masini, F., Puchinger, J., & Ruthmair, M. (2016). *Overview of optimization problems in electric carsharing system design and management*. Springer.

Duong, V.-H., Bastawrous, H. A., Lim, K., See, K. W., Zhang, P., & Dou, S. X. (2015). Online state of charge and model parameters estimation of the lifepo4 battery in electric vehicles using multiple adaptive forgetting factors recursive least-squares. *Journal of Power Sources*, *296*, 215–224.

Espinoza, P. A., Pérez, A., Orchard, M., Navarrete, H., & Pola, D. (2017). A simulation engine for predicting state-of-charge and state-of-health in lithium-ion battery packs of electric vehicles.

Garcia-Valle, R., & Lopes, J. A. P. (2012). *Electric vehicle integration into modern power networks*. Springer Science & Business Media.

Hu, X., Jiang, J., Cao, D., & Egardt, B. (2016). Battery health prognosis for electric vehicles using sample entropy and sparse bayesian predictive modeling. *IEEE*

Transactions on Industrial Electronics, *63*(4), 2645–2656.

Jensen, A. F., & Mabit, S. L. (2017). The use of electric vehicles: A case study on adding an electric car to a household. *Transportation Research Part A: Policy and Practice*, *106*, 89–99.

Jungnickel, D. (2013). *Graphs, networks and algorithms* (4th ed., Vol. 5). Springer-Verlag Berlin Heidelberg.

Musso, C., Oudjane, N., & Le Gland, F. (2001). Sequential monte carlo methods in practice. , 247–260.

Orchard, M. E., & Vachtsevanos, G. J. (2009). A particle-filtering approach for on-line fault diagnosis and failure prognosis. *Transactions of the Institute of Measurement and Control*, *31*(3-4), 221–246.

Pelletier, S., Jabali, O., & Laporte, G. (2016). 50th anniversary invited articlegoods distribution with electric vehicles: review and research perspectives. *Transportation Science*, *50*(1), 3–22.

Pelletier, S., Jabali, O., Laporte, G., & Veneroni, M. (2017). Battery degradation and behaviour for electric vehicles: Review and numerical analyses of several models. *Transportation Research Part B: Methodological*, *103*, 158–187.

Pola, D. A., Navarrete, H. F., Orchard, M. E., Rabié, R. S., Cerda, M. A., Olivares, B. E., ... Pérez, A. (2015). Particle-filtering-based discharge time prognosis for lithium-ion batteries with a statistical characterization of use profiles. *IEEE Transactions on Reliability*, *64*(2), 710–720.

Shao, S., Guan, W., Ran, B., He, Z., & Bi, J. (2017). Electric vehicle routing problem with charging time and variable travel time. *Mathematical Problems in Engineering*, *2017*.

Sun, F., Xiong, R., & He, H. (2016). A systematic state-of-charge estimation framework for multi-cell battery pack in electric vehicles using bias correction technique. *Applied Energy*, *162*, 1399–1409.

Sweet, A., Gorospe, G., Daigle, M., Celaya, J. R., Balaban, E., Roychoudhury, I., & Narasimhan, S. (2014). *Demonstration of prognostics-enabled decision making algorithms on a hardware mobile robot test platform* (Tech. Rep.). SGT Inc. Moffett Field United States.

Yen, J. Y. (1971). Finding the k shortest loopless paths in a network. *management Science*, *17*(11), 712–716.

Zou, Y., Hu, X., Ma, H., & Li, S. E. (2015). Combined state of charge and state of health estimation over lithium-ion battery cell cycle lifespan for electric vehicles. *Journal of Power Sources*, *273*, 793–803.

BIOGRAPHIES

Heraldo Rozas is M.Sc. student in Electrical Engineering at the University of Chile. Currently he is a Research Assistant at the Fault Diagnosis and Failure Prognosis Laboratory of the University of Chile. His research interests include Decision-Making under uncertainty, Diagnostic and Prognostic of faults.

Diego Muñoz-Carpintero obtained his BSc and MSc degrees in Electrical Engineering in 2009 and 2010, respectively, both from the Universidad de Chile, and received a DPhil in Control Engineering in 2014 from the University of Oxford. From 2015 to 2016 he was a Research Fellow at Nanyang Technological University, and since 2017 he holds a Researcher position at the University of Chile. His research interests include: control theory in the areas of predictive, robust and stochastic control; intelligent control; decision making under uncertainty; and their application to energy efficient systems.

Aramis Perez received his B.Sc. degree and Licentiate degree in Electrical Engineering from the University of Costa Rica. He received his master degree in Business Administration with a General Management Major from the same university. He also received the Doctorate in Electrical Engineering degree from the University of Chile. Currently he is a Research Fellow at the Fault Diagnosis and Failure Prognosis Laboratory and the Energy Center of the University of Chile. Also,he is a Professor at the School of Electrical Engineering at the University of Costa Rica. His research interests include parametric/non-parametric modeling, system identification, data analysis, and manufacturing processes.

Kamal Medjaher is Full Professor at Tarbes National School of Engineering (ENIT), France, since February 2016. He conducts his research activities within the Production Engineering Laboratory (LGP). Before this position, he was Associate Professor at the National Institute of Mechanics and Microtechnologies in Besanon, France, from September 2006 to January 2016. After receiving an engineering degree in electronics, he received his MS in control and industrial computing in 2002 at Ecole Centrale de Lille and his PhD in 2005 in the same field from University of Lille 1. Since September 2006, Kamal Medjaher leads research works in the field of Prognostics and Health Management of industrial systems.

Dr. Marcos E. Orchard received the B.S. degree and a Civil Industrial Engineering degree with electrical major from Catholic University of Chile. He also received the M.S. and Ph.D. degrees from The Georgia Institute of Technology, Atlanta, GA, USA. He is currently an Associate Professor with the Department of Electrical Engineering, and the head of the Fault Diagnosis and Failure Prognosis Laboratory at the University of Chile. His current research interest is the design, implementation and testing of real-time frameworks for fault diagnosis and failure prognosis, with applications to battery management systems, mining industry, and finance.