

Planning an Itinerary for an Electric Vehicle

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Abstract— The steady increase in oil prices and awareness regarding environmental risks due to carbon dioxide emissions are promoting the current interest in electric vehicles. However, the current relatively low driving range (autonomy) of these vehicles, especially compared with the autonomy of existing internal combustion vehicles, remains an obstacle to their development. In order to reassure a driver of an electric vehicle and allow him to reach his destinations beyond the battery capacity, we describe a system which generates an energy plan for the driver. We present in this paper the electric vehicle ecosystem and we focus on the contribution of using the generalized multi-commodity network flow (GMCNF) model as a vehicle routing model that considers energy consumption and charging time in order to ensure the usage of an electric vehicle beyond its embedded autonomy by selecting the best routes to reach the destination with minimal time and/or cost. We also present some perspectives related to the utilization of autonomous electric vehicles and wireless charging systems. We conclude with some open research questions.

Keywords: Electric Vehicle, Energy Plan, Generalized Multi-Commodity Network Flow, Autonomous Vehicle.

I. INTRODUCTION

The steady increase in oil prices and awareness regarding environmental risks posed by emissions of Carbon Dioxide (CO₂) are promoting the current interest in Electric Vehicles (EVs). However, the relatively low driving range (autonomy) of these vehicles, especially compared with the autonomy of existing internal combustion vehicles, remains an obstacle to their development. Indeed, many drivers could be afraid to live in constant fear of the failure to not reach their destinations using their vehicles, and to be limited in their movements on long distances between cities, for example.

In order to reassure a driver of an EV and allow him to reach his destinations beyond the battery capacity, we describe a system which generates a smart energy plan for the driver. This energy plan consists of roads connecting service stations to the destination. Each service station may be a quick charging station or a battery exchange station. While we can

also take into account hybrid vehicles by considering traditional stations (gas and oil), we focus in this paper on EVs. The autonomy of an EV is sensitive to many factors. Indeed, the energy consumption by an EV is driven by multiple internal and external parameters of the vehicle. The system presented in this paper provides a driver with a reliable driving plan thanks to its model of autonomy calculation and network analysis.

II. BACKGROUND

Like in many other places in the world, the European Commission expects that energy needs will continue to increase. In the case of European Union, primary energy consumption in 2030 would be 11% higher than in 2005 [1]. According to the European Environment Agency, road transport is a large consumer, accounting for the most significant part (around 72%) of the total transport energy consumption [2]. The European Commission also expects 1.6 billion vehicles in the world in 2030 and 2.5 billion in 2050 [3]. These numbers are not surprising given the projected population growth in the world and the differences in the density of vehicles (number of vehicles per 1000 inhabitants) between countries that are going to shrink (for example, 627 in USA, 44 in China, and 12 in India, in 2010 [4]). On another hand, personal vehicles (internal combustion engine vehicles) are responsible for 10% of CO₂ emissions in the atmosphere [5]. For all these reasons, EVs could bring a significant contribution to the World policies for sustainable development, both in the ecological and energy-related sides by reducing CO₂ (and other pollutants such as Nitrogen Oxide (NO_x), Hydrocarbon (HC), and Carbon Monoxide (CO)) emissions [6] and non-renewable energy consumption¹.

¹ By assuming that electricity should be produced using renewable sources such as hydro, solar, wind, waves, etc.

Interesting research studies [7][8] have been conducted in this context to show the contribution of EVs (and also hybrid vehicles) in reducing CO2 emissions and energy consumption in the USA. A study conducted by CIRE² focused on macroeconomic and macro-energetic aspects of the deployment of EVs [9]. Results show that this deployment can positively influence the economy, particularly in scenarios considering climate policy and tensions on oil prices, but also that EVs allow a significant reduction in CO2 emissions from private transport.

Furthermore, the future of EVs could be promising in the economical side. Target markets in the short term represent mainly owners of vehicles for which autonomy is not a particular problem. This represents more than 70% market share [10], given, for example, that 87% of Europeans drive less than 60 kilometers per day [6].

However, EVs represent more disruptive innovative products compared to the traditional vehicles. The emerging of new services requires considering the EVs and the surrounding environment during their whole lifecycle. An interesting study has been presented in [11][12][13], showing the EVs' ecosystem and explaining complex interfaces between the surrounding stakeholders. We report the EVs' environment modeling in Fig. 1.

There are a lot of issues to be addressed. We focus in the present study on the contribution of autonomy calculation and network problem solving in order to ensure the usage of an EV beyond its embedded autonomy by selecting the best routes to reach the destination with minimal time and/or cost.

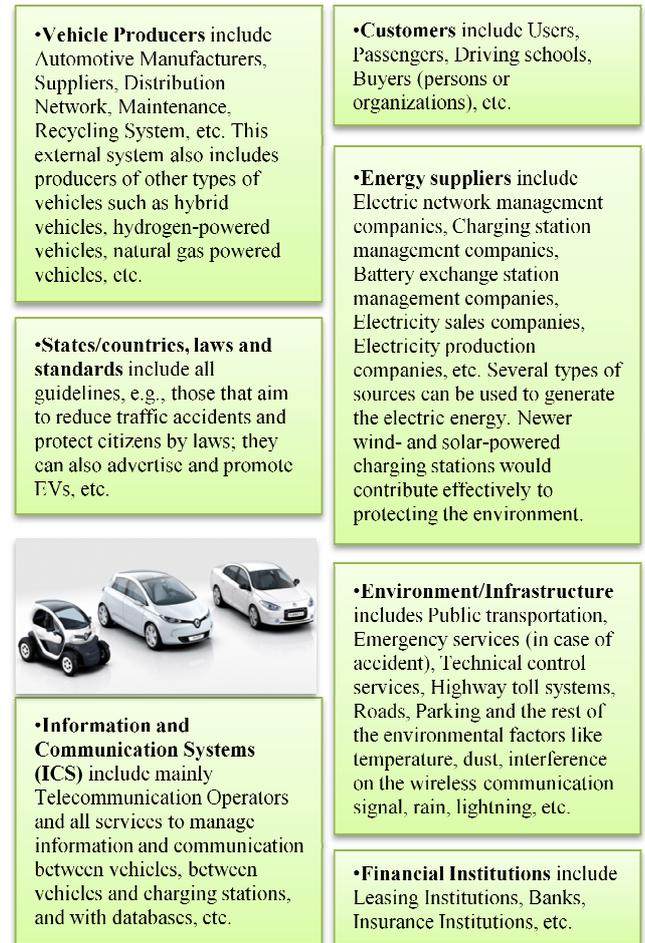


Fig. 1. EVs' ecosystem [13].

III. SYSTEM OF INTEREST DESCRIPTION

We describe in the following paragraph a simplified example and a generic structure of our system of interest and the modules that are necessary and useful for its implementation. It allows the vehicle driver to easily determine, taking into account the current battery level, at least one path connecting the current location of the vehicle (A) to the destination (B), the transit time, and the cost. This trip may involve steps for battery charging or exchange. To do this, the driver shall first submit a mission by designating a destination (B) using a Human Machine Interface (HMI), which can be integrated permanently in the dashboard or can be mobile through a wireless link like a smart-phone. The energy consumption module then retrieves information about the current location (A), the current battery level, and energy required for a trip from A to B. The path calculation module retrieves all the parameters needed for the mission: the coordinates of charging stations on paths between A and B, their electrical characteristics, weather and traffic conditions on these paths, etc. This module calculates the conditions for success of the mission taking into account the battery level throughout the trip, the time required to achieve the mission, and the cost depending on the eventual choice of energy

² CIRE²: Centre International de Recherche sur l'Environnement et le Développement, France. <http://www.centre-cired.fr/>

supplier by the driver. If the mission cannot be achieved without steps, this module provides a map of charging stations on the best route(s) with additional information of a particular energy supplier such as tariffs.

A. Generic structure

Figure 2 summarizes a generic structure of our proposition. We assume that the vehicle can get information through the Internet via a wireless connection, including the type of road and weather conditions, traffic congestion, GPS position of charging stations, etc.

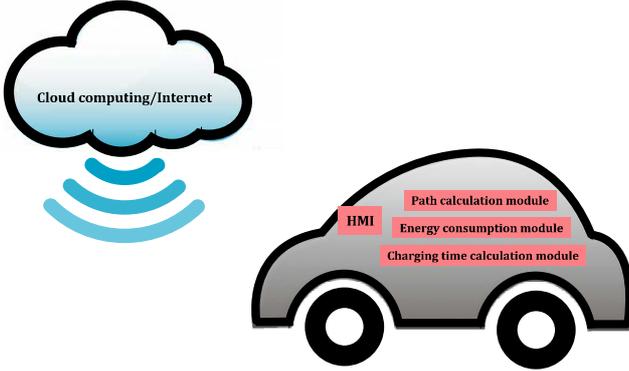


Fig. 2. A generic structure of the system of interest.

B. Human Machine Interface (HMI)

As mentioned previously, the HMI can be integrated permanently in the dashboard or can be mobile through a wireless link like a smart-phone. Using this HMI, a user of the vehicle can plan a mission or trip and choose a path based on his preference between time, cost, and other factors.

C. Path calculation module

One of the objectives of the path calculation module is to find a trip from point A to point B with minimal time and/or cost. For a round-trip mission, A is also a final destination but B still has to be defined as a halfway point. Figure 3 illustrates, in the form of a graph consisting of nodes and edges, an example network of different paths connecting A and B, based on which our system estimates time and cost. In Figure 3, four points 1 through 4 may be a step of battery charging or exchanging during a trip from A to B. Each edge ij represents a driving route from node i to node j , where $i, j = \{A, 1, 2, 3, 4, B\}$. Driving time from i to j is denoted as t_{ij} .

If the problem is to minimize the total time and there is no waiting at each transit node, it is called the shortest path problem and can be solved using conventional techniques such as Dijkstra's algorithm as it was addressed in [16]. In the problem to be addressed in this paper, however, the vehicle might have to stay for a while at a transit node to charge or exchange the battery. This process takes extra time, which should be considered in addition to the driving time. In Figure 3, each transit node is attached with a "loop", which represents charging or exchanging of the battery. Charging/exchanging time at node i is denoted as t_{ii} .

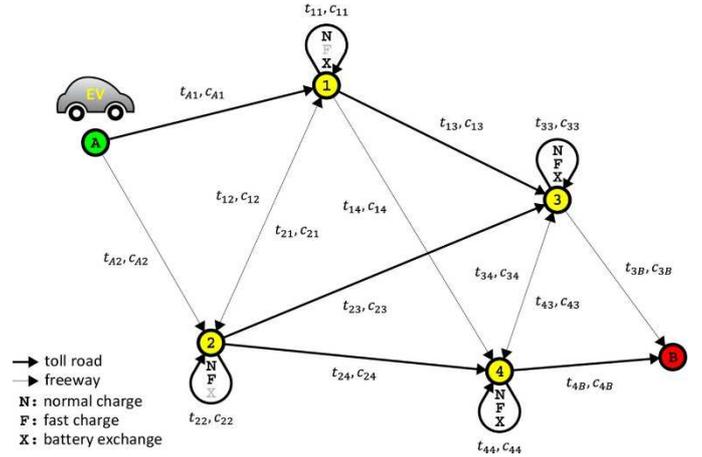


Fig. 3. An example network of different paths connecting A and B.

Furthermore, if the battery charging or exchanging cost is also considered, each loop has a cost c_{ii} . It should be noted that the vehicle does not necessarily have to charge or exchange the battery at every node that it passes through. Therefore, whether the vehicle changes/exchanges the battery at each transit node is also to be determined through the optimization process performed by this module. Additionally, if a toll is required on each edge, c_{ij} can represent that cost.

This type of optimization problem can be formulated as the generalized multi-commodity network flow (GMCNF) problem. It is a novel network flow model that introduces three types of matrix multiplications (requirement, transformation, and concurrency) on top of the classical network flow problems and also allows loop edges associated with nodes (graph loops) and multiple edges between the same end nodes (multigraph) [14][13]. The problem in this paper can be interpreted as a shortest path problem with internal sources of consumables. The similar type of problem is discussed in the GMCNF case study of space exploration logistics [15].

Let $G = (\mathcal{N}, \mathcal{A})$ be a directed network defined by a set \mathcal{N} of nodes and a set \mathcal{A} of directed edges. Each node $i \in \mathcal{N}$ is associated a vector \mathbf{b}_i representing its net supply/demand. The GMCNF problem can be formulated as follows:

Minimize

$$J = \sum_{(i,j) \in \mathcal{A}} J_{ij}^{\pm}$$

subject to

$$\begin{aligned} \sum_{j:(i,j) \in \mathcal{A}} \mathbf{A}_{ij}^+ \mathbf{x}_{ij}^+ - \sum_{j:(j,i) \in \mathcal{A}} \mathbf{A}_{ji}^- \mathbf{x}_{ji}^- &\leq \mathbf{b}_i \quad \forall i \in \mathcal{N} \\ \mathbf{B}_{ij} \mathbf{x}_{ij}^+ &= \mathbf{x}_{ij}^- \quad \forall (i,j) \in \mathcal{A} \\ \mathbf{C}_{ij}^+ \mathbf{x}_{ij}^+ &\leq \mathbf{0} \quad \text{and} \quad \mathbf{C}_{ij}^- \mathbf{x}_{ij}^- \leq \mathbf{0} \quad \forall (i,j) \in \mathcal{A} \\ \mathbf{0} \leq \mathbf{x}_{ij}^+ &\leq \mathbf{u}_{ij}^+ \quad \text{and} \quad \mathbf{0} \leq \mathbf{x}_{ij}^- \leq \mathbf{u}_{ij}^- \quad \forall (i,j) \in \mathcal{A} \end{aligned}$$

where x_{ij}^+ and x_{ij}^- represent an outflow from node i to edge ij and an inflow from edge ij into node j , respectively. A_{ij}^\pm , B_{ij} , and C_{ij}^\pm are called a requirement matrix, a transformation matrix, and a concurrency matrix, respectively. If time and/or cost on each edge includes a fixed term (regardless of amount), a binary variable z_{ij} needs to be introduced, which is equal to 1 if the vehicle passes through edge ij and 0 if not. In this case, the problem falls under the mixed integer linear program (MILP).

Parameters that define each edge and loop such as energy required for passing through an edge and time required for charging the battery at a loop could be determined in the modules described below.

D. Energy consumption module

The module for calculating energy consumption of an EV uses not only the internal parameters of the vehicle but also the external parameters retrieved from cloud computing/Internet. By default, the model of energy consumption of an EV minimizes the energy required to reach the destination. But the driver can also choose to focus on prices at charging stations to minimize the cost.

Some internal parameters of the vehicle, reflected in the model of energy consumption of an EV, include internal temperature of the battery, the laws of control for battery and electric motor cooling, the auxiliary consumers like headlights, air conditioning or heating, the mass of the vehicle, its coefficient of air penetration (aerodynamics) or the size of the wheels. Other data such as battery weight, storage capacity of the battery, nominal output voltage of battery, the characteristics of the motor or motors (torque, rotation speed of the engine, etc.), and gear ratio are also considered.

External parameters can be constraints on road (traffic congestion) and weather conditions, slope of the roads, acceleration of gravity, air density, temperature, air pressure, the driving profile of the user, the distance, etc.

Given all these parameters, we can calculate the EV autonomy. For this purpose, the driving cycle of the user is very important. In the following simplistic example, we consider the calculation of energy consumption over a distance as an average of the energy consumption using the standards NEDC and Artemis as explained in [17]. In addition, we take into account a threshold for safety (a capacity for driving about 15 km for example is always left in the battery). Note, as explained in [17], the EV energy consumption represents the sum of the energy consumed by all the components of its electric vehicle power-train (considering the performance of all its components) and by the auxiliaries, such as lights, air conditioning system and radio...). Figure 4 gives an example of results using the initial parameters presented in [17].

Details for calculating the autonomy and a case study are presented in [16][17][18].

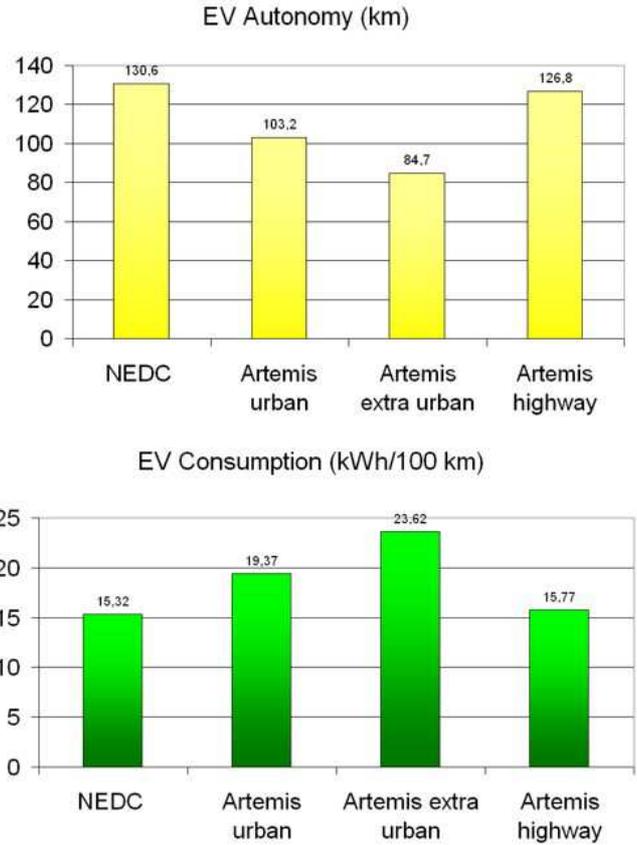


Fig. 4. The EV autonomy and energy consumption estimations [17].

E. Charging time calculation module

As described in more detail in [16], in order to improve the accuracy of the estimated travel time, the consumption module also includes calculating the charging time, either fast charge or normal charge, taking into account not only the amount of charge but also the internal battery temperature and the outside temperature at the load point. The temperatures influence the time required to reach full charge.

The charging time is a function T , using as inputs the intensity of the electric current I and the capacity of the battery C .

We want to charge the battery, in the station i , with a capacity C necessary and sufficient to achieve at least the section between the station i and the next station j . If the time we can spend at j will not be enough to charge the battery to reach yet another subsequent station k , we must charge the battery more at i .

The capacity C reflects the energy consumed by the vehicle in a section. It represents the sum of the energy consumed by the power-train and by the auxiliaries.

In summary, the time of charge depends on the charging system's characteristics. For an example in the next section, we consider the following estimates:

- A normal charging system using standard outlet 240 Volt: 12 minutes (and \$0.15) per 1 kWh.
- A fast charging system: 1,5 minutes (and \$0.25) per 1 kWh.
- Battery exchange: 3 minutes (and \$10).

IV. EXAMPLE

This section presents an example problem for finding the best route of a single EV from A to B in the network in Fig. 3 using the GMCNF method described above. We assume 24 kWh for the full capacity of a single battery and 2 kWh for the minimum allowed battery level for path calculation. Table I lists various edge parameters used in the analysis.

Table I. Edge parameters for the example network in Fig. 3.

node i	node j	type	distance [km]	driving time [min]	energy consumption [kWh]	toll [USD]
A	1	toll	45	30	8.1	13.5
A	2	free	40	40	7.2	0
1	2	free	55	55	9.9	0
1	3	toll	50	35	9.0	15.0
1	4	free	70	70	12.6	0
2	1	free	55	55	9.9	0
2	3	toll	70	45	12.6	21.0
2	4	toll	60	40	10.8	18.0
3	4	free	35	35	6.3	0
3	B	free	45	45	8.1	0
4	3	free	35	35	6.3	0
4	B	toll	35	25	6.3	10.5

The objective is to minimize the total time and/or cost. Assuming a linear objective function, the problem is a linear program and a contribution from edge ij to the overall objective function is written as:

$$J_{ij} = (w_t t_{ij} + w_c c_{ij}) x_{ij}$$

where w_t and w_c are objective function weights for time and cost, respectively. The edge parameters in Table I and the battery charging/exchanging time and cost are implemented in c_{ij}^\pm and two matrices, B_{ij} and C_{ij}^\pm . Note that A_{ij}^\pm is an identity matrix because there is no such constraint in this context. For edge ij , B_{ij} models energy consumption while C_{ij}^\pm models constraints on the full battery capacity and the minimum allowed battery level for path calculation. For loop ii , B_{ii} models battery charge/exchange.

Varying the weights between time and cost, we obtained five different Pareto-optimal solutions. Using a normal store-bought laptop computer, the optimal solution in each instance was obtained within 0.1 seconds at most. Figure 5 shows the five “best” paths from A to B. Path 1 in the top minimizes solely the transit time while path 5 in the bottom minimizes solely the total cost. Each of the paths 2-4 minimizes a mix of time and cost with different weights. Paths 1 and 2 look the same in path topology but path 1 exchanges the battery at station 4 while path 2 uses the fast charging system at the same station. Likewise, Paths 4 and 5 look the same in path topology but path 4 mainly uses fast charge while path 5 only uses normal charge. Figure 6 shows the Pareto-optimal front for the time-cost trade-off. While paths 2-4 appear to be more reasonable options, a driver of the vehicle can choose any of these candidates based on his preference.

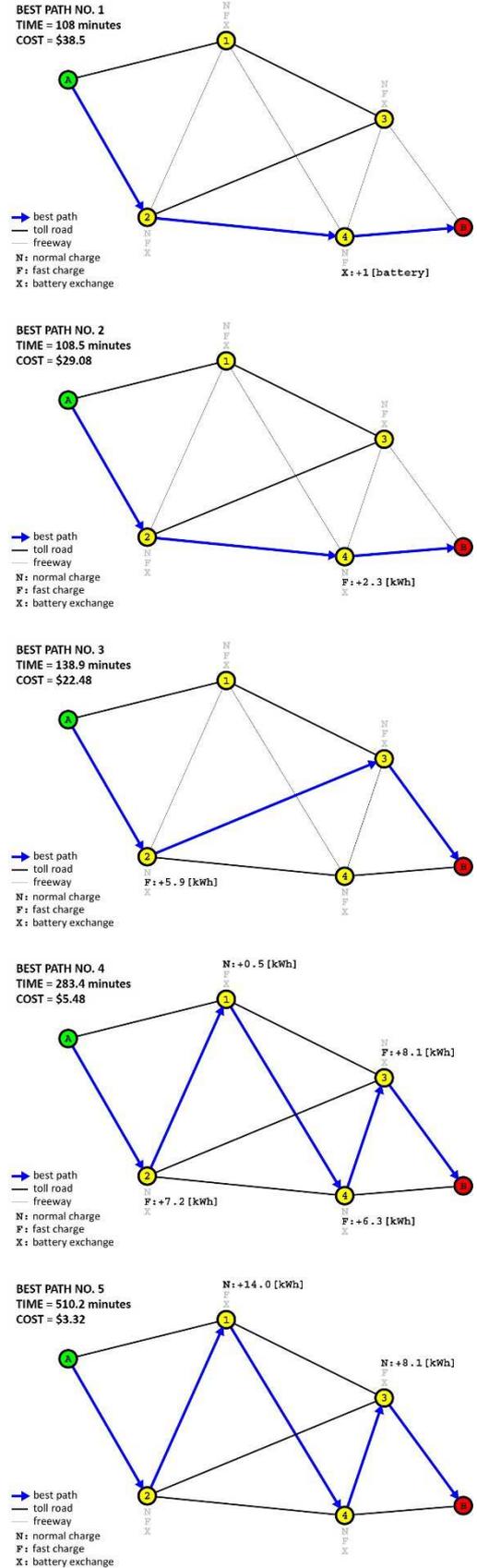


Fig. 5. Five different “best” paths from A to B.

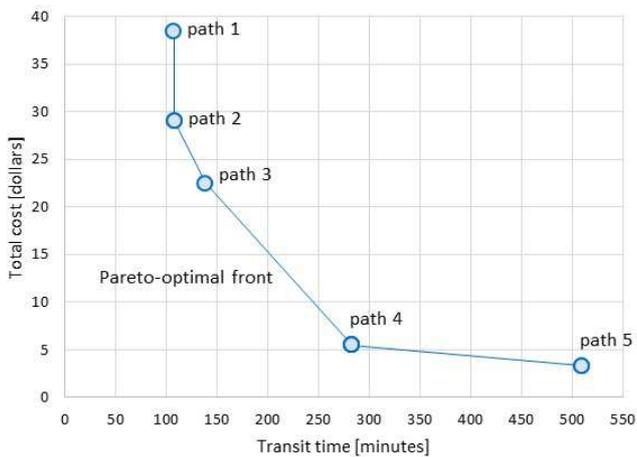


Fig. 6. The Pareto-optimal front for the time-cost trade-off.

V. APPLICATION TO AUTONOMOUS VEHICLES

A direct application of the mission planner presented above could be its use for autonomous vehicles based on electric vehicles. The concept seems indeed like a natural or logical fit for this type of autonomous systems, for which some kind of “global planning” or mission definition is necessary. The implementation of this type of mission planner can be done either as an embedded or as an off-board capability of the system.

In the case of EVs, the mission planner dedicated to the optimization of the vehicle autonomy could run permanently even while the vehicle has already started its *mission*, that is, while it is navigating towards a destination point B as defined by a user. The autonomous system would then endeavor to satisfy its mission (i.e. reach point B), autonomously deciding to change its path if needed in order to maintain its autonomy at a satisfactory level.

Finally, the mission planner could also contribute to the optimization of the number of charging stations, in the perspective of wireless (or induction) charging techniques. A “charging system” could then make use of V2I (Vehicle to Infrastructure) or V2V (Vehicle to Vehicle) communications in order to inform autonomous vehicles on the schedule or the availability of recharge stations or even to coordinate and program their utilization.

VI. CONCLUSION AND PERSPECTIVES

We have addressed in this paper the contribution of autonomy calculation and network modeling in order to help EVs’ drivers to enhance their utilization of EVs in a good way, by reducing time waste and cost. Indeed, beyond the capacity of the current batteries, the drivers of EVs could plan, a priori, their different missions or trips through a simple HMI.

However, there are a lot of open research questions to be addressed in the future such as the management of battery charging/exchanging stations (How do we handle the arrival flow of EVs? How many stations are necessary and sufficient in a given area? How do we charge an EV at home or in a parking lot if they have not been designed to allow that? etc.), the management of electric grid (How do we manage demand

peaks of electrical energy?), the ability to level energy demands on the energy network (see for example [19][19] about the use of EVs for “Vehicle to grid”), and the management of interfaces with customers (How do we deal with bills? How do we address remote HMI for charging reservations? etc.). Also, the complex economic equation and business model and taxes related to EVs should be addressed.

Indeed, beyond the energy and ecological issues, EV programs are yielding waves of innovations and job opportunities. Many key actors or stakeholders in the EVs’ ecosystem are involved in the implementation of infrastructures and associated services. Indeed, given the fact that these programs have been started almost from scratch, the knowledge of all stakeholders surrounding the EVs throughout their whole lifecycle is paramount. For each of these stakeholders, the knowledge of his expectations and needs helps greatly in well designing the EVs and associated services in order to best integrate them sustainably in their environment. These stakeholders should probably cooperate and join unique structures, where each contributes with his own competence to meeting the EVs’ success.

We assist today at many emerging partnerships between EVs’ manufacturers and energy companies, telecom companies, parking owners, etc. New operators are appearing (new business models such as car sharing). For a long term, in order to build sustainably this new market for EVs, national/regional organizations would drive and organize the cooperation of their industries (public and private) with local authorities.

REFERENCES

- [1] *European Energy and Transport – Trends to 2030*. European Commission- Directorate-General for Energy and Transport. 2007.
- [2] *Final Energy Consumption by Sector 2010*. Official document of European Environment Agency, available online <http://www.eea.europa.eu/data-and-maps/indicators/transport-final-energy-consumption-by-mode/> 2010.
- [3] *Vers l’automobile décarbonnée*. Handbook, La Chambre Syndicale Internationale de l’Automobile et du Motocycl, France. Editions 2010
- [4] Statistiques mondiales -. http://www.statistiques-mondiales.com/voitures_particulieres.htm, November 2010
- [5] World Ressources Institute. (cf, *Vers l’automobile décarbonnée*, publication - Chambre Syndicale Internationale de l’Automobile et du Motocycle). Editions 2010.
- [6] R. Bastien, *The Electric Vehicle Program of the Renault-Nissan Alliance*, in Automotive Electronics and Systems Congress CESA, Electric and Hybrid Vehicles, Paris, November 2010.
- [7] J. Heywood, P. Baptista, I. Berry, K. Bhatt, L. Cheah, F. Sisternes, V. Karplus, D. Keith, M. Khusid, D. MacKenzie and J. McAulay, *An Action Plan for Cars: The Policies Needed to Reduce U.S. Petroleum Consumption and Greenhouse Gas Emissions*. MIT Energy Initiative, Cambridge, Massachusetts. December 2009.
- [8] V. Karplus, *Prospects for Plug-In Hybrid Transportation in the United States: A General Equilibrium Analysis*. Master of Science Thesis, Technology and Policy Program, and Dept. of Civil and Environmental Engineering, MIT, 2008.
- [9] A. Vogt-Schilb, O. Sassi C. Cassen and J.C. Hourcade, *Electric vehicles: What economic viability and climate benefits in contrasting futures?* Report of Centre International de Recherche sur l’Environnement et le Développement, CIRED October 2009. (Available online on <http://www.centre-cired.fr/IMG/pdf/electricvehicule.pdf>, accessed March 2011).
- [10] C. Ghosn, Renault-Nissan CEO interview, 30 September 30th, 2010. <http://www.rtl.fr/actualites/vie-pratique/article/carlos-ghosn-au->

mondial-de-l-auto-renault-lance-les-commandes-des-voitures-electriques-5953121278.

- [11] A. Doufene. *Architecture des systèmes complexes et Optimisation. Application aux véhicules électriques*. PhD Thesis, Ecole Polytechnique, France. March 2013.
- [12] A. Doufene, H.G. Chalé-G and D. Krob. *Sharing the Total Cost of Ownership of Electric Vehicles: A Study on the Application of Game Theory*. International communication in the 23rd Annual INCOSE International Symposium – Philadelphia USA. 24-27 June, 2013.
- [13] A. Doufene, H.G. Chalé G., A. Dauron and D. Krob. *Model-Based operational analysis for complex systems - A case study for electric vehicles*. International communication in the 24rd Annual INCOSE International Symposium – Las Vegas, USA. June 2014.
- [14] T. Ishimatsu, *Generalized Multi-Commodity Network Flows: Case Studies in Space Logistics and Complex Infrastructure Systems*, PhD Thesis, Dept. of Aeronautics and Astronautics, MIT, 2013.
- [15] T. Ishimatsu, O. de Weck, J. Hoffman, Y. Ohkami, and R. Shishko. *A Generalized Multi-Commodity Network Flow Model for Space Exploration Logistics*. AIAA SPACE 2013 Conference & Exposition – San Diego, USA. September 2013.
- [16] Patent - *Method and device for mission and destination validation for an electric or hybrid vehicle* Institut National de la Propriété intellectuelle (INPI- France) and European Patent Organization (EPO). 2012.
- [17] A. Doufene, H.G. Chalé-G. and D. Krob. *Complex Systems Architecture Framework. Extension to Multi-Objective Optimization*. International conference, Complex Systems Design & Management (CSDM), Paris December 2012. Proceedings "Science and Engineering" series by Springer.
- [18] Janiaud N. 2011. "Modélisation du système de puissance du véhicule électrique en régime transitoire en vue de l'optimisation de l'autonomie, des performances et des coûts associés". PhD thesis, SUPELEC, France.
- [19] W. Kempton and J. Tomic, *Vehicle-to-grid power implementation: From stabilizing the grid to supporting large-scale renewable energy*, Journal of Power Sources, Volume 144, Issue 1, Pages 280-294, 1 June 2005.