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# A new model for electric vehicle mobility and energy consumption in urban traffic networks

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## SHORT SUMMARY

This paper introduces a new model for electric vehicle mobility and energy consumption in urban traffic networks. The model couples the vehicle mobility described by a set of ODEs over a graph capturing the Origin-destination motion for urban networks, and the energy consumption associate to this mobility patterns. This model is illustrated in a simple pedagogic example showing its capabilities, such as keeping track of the vehicle state of charge, current energy and available storage.

**Keywords:** Urban mobility, Electric vehicles, Energy requirements

## 1 INTRODUCTION

As concerns for environmental protection become a major concern, Electric Vehicles (EVs) have started to rise as one of the main components of sustainable traffic systems in cities worldwide. Indeed, some countries have started to incorporate plans to phase-out conventional fuel vehicles in the following years, in efforts to reduce carbon emissions. However, this shift towards an electrified traffic network implies several challenges that need to be solved for EVs to become mainstream. From the consumer side, one of the most common complaints about EVs is the lack of sufficient charging stations so that they can conveniently have their day-to-day life. From the side of city officials and stakeholders, EVs could have a large impact on the power network infrastructure by overloading congested nodes, but at the same time, EVs can be actively used to benefit the power network if Vehicle-to-Grid connections become standard. Initiatives in that directions have been already taken in cities like Utrecht, which has become a proving ground for the bidirectional-charging techniques that have the rapt interest of automakers, engineers, city managers, and power utilities the world over (see <https://spectrum.ieee.org/vehicle-to-grid>)

To be able to address these problems, it is first needed to model the power needs and energy consumption of EVs in time and space, which are linked to the mobility patterns of people in urban areas as they go through their regular lives. In this paper, we propose a model that couples urban human mobility, the separation of people flows into several transportation modes including EVs, and an energy model, such that a holistic view of EVs can be given. The model is described and instantiated using a simple network of only two nodes, however, the model is general and applicable to any dimension. In simulations, we show the evolution of people flows, population, power losses, current energy and available storage in each location.

## 2 METHODOLOGY

To understand the energy needs and effects of a given penetration rate of EVs, we must first understand the space-and-time-dependent mobility patterns of people in an urban area. For this purpose we consider the mobility model first proposed in (Niazi et al., 2021), which considers the

mobility between two location types: origins and destinations. The former corresponds to areas where people reside, whereas the latter corresponds to locations that people visit during the day for different activities such as work, education, leisure, commerce, etc. Consider the simple example in Fig. 1 consisting of only one origin (node 1) and one destination (node 2).

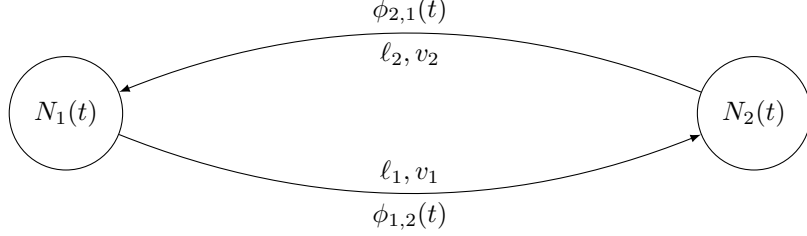


Figure 1: Simple network example: mobility between one origin and one destination

The mobility model allows to describe the evolution of the population in each node  $N_1(t)$ ,  $N_2(t)$ , and the flows of people between them at each time. The model is based in a set of coupled conservation Ordinary Differential Equations (ODEs) of the form

$$\dot{N}_1(t) = \phi_{2,1}(t) - \phi_{1,2}(t) \quad , \quad \dot{N}_2(t) = \phi_{1,2}(t) - \phi_{2,1}(t) \quad (1)$$

where the parameters  $\ell_i$  and  $v_i$  ( $i = 1, 2$ ) describe the distance and average speed of each trajectory between the nodes, and  $\phi_{1,2}$  is the flow (people per hour) going from node 1 to node 2. This flow is defined as

$$\phi_{1,2}(t) = \min\{D_{1,2}(t), S_2(t)\} \quad (2)$$

where the Demand of the origin 1 to the destination 2  $D_{1,2}$  is given by

$$D_{1,2}(t) = \delta_{1,2}(t)M_{1,2} \quad (3)$$

where  $\delta_{1,2}(t) \in [0, 1]$  is called the demand gating function and describe the time window during the day where the population start to leave to destination.  $M_{1,2}$  is the number of people that want to go from 1 to 2 during the day. Similarly, the Supply of node 2  $S_2(t)$  is given by

$$S_2(t) = \begin{cases} \psi_2(t)\phi_2^{max} & \text{if } N_2(t) < N_2^{max} \\ 0 & \text{else} \end{cases} \quad (4)$$

where  $\psi_2(t) \in [0, 1]$  is the supply gating function indicating the time window where destination is available during the day.  $\delta_{1,2}(t)$  and  $\psi_2(t)$  can be different during the working days and the weekends.  $N_2^{max}$  is the capacity of node 2, and  $\phi_2^{max}$  is the maximum inflow to node 2. The flow from node 2 to 1  $\phi_{2,1}$  is defined analogously. Although here we only describe the equations for 2 nodes, this model is applicable to any number of origin and destination nodes. An extended version of the model and its application, parameter calibration, and discretization strategy for the case of the city of Grenoble in France can be found in (Pratap et al., 2022).

To use the information regarding the mobility flows for the case of EVs, it is required to determine what is the proportion of people making each trip using a private car, public transport, cycling, walking, etc. This problem is known as the modal choice (or mode choice) analysis, for which there is a lot of interest and attention in the literature, see of instance (Bouscasse et al., 2019) and (Mondal & Bhat, 2022). We consider in this work the well-known logit model, which computes the probability that a person uses their private vehicle as

$$p^{car}(\mathbf{x}, \beta_1, \dots, \beta_m) = \frac{1}{1 + \sum_{n=1}^m \exp(\beta_n \cdot \mathbf{x})} \quad (5)$$

where  $\mathbf{x} \in \mathbb{R}^q$  are descriptor variables related to the trip properties (traveling time per mode, distance, trip cost per mode, etc.),  $\beta_n \in \mathbb{R}^q$  ( $n = 1, 2, \dots, m$ ) are mode-dependent parameters for each of the other transport modes (public transport, bicycle, etc.), and  $m$  is the number of modes other than the private car. For real applications, parameter calibration is done using data from public household surveys.

Once the number of cars doing each trip is known, the corresponding number of EVs can be computed using the penetration rate  $\eta^{EV}$ . Thus, we can describe the number of EVs at node 1 ( $N_1^{EV}$ ) as

$$\dot{N}_1^{EV}(t) = \phi_{2,1}^{EV}(t) - \phi_{1,2}^{EV}(t) \quad (6)$$

where

$$\phi_{1,2}^{EV}(t) = \eta^{EV} p^{car}(\mathbf{x}_{1,2}, \boldsymbol{\beta}_1, \dots, \boldsymbol{\beta}_m) \phi_{1,2}(t). \quad (7)$$

The flow  $\phi_{2,1}^{EV}$  and the number of EVs at node 2  $N_2^{EV}$  are defined using analogous equations with the corresponding changes in subindices.

Furthermore, it is required to model available electric vehicle energy and power consumption in each location. We denote the average state of charge of vehicles at node 1 as  $\varepsilon_1 \in [0, 1]$ , and the average battery net capacity of all EVs in the network as  $C$  (kWh). The energy in each node is then defined as

$$E_1(t) = CN_1(t)\varepsilon_1(t) \quad , \quad E_2(t) = CN_2(t)\varepsilon_2(t). \quad (8)$$

The evolution of the energy in each location can also be described using a conservation ODE,

$$\dot{E}_1(t) = P_1^{in}(t) - P_1^{out}(t) \quad , \quad \dot{E}_2(t) = P_2^{in}(t) - P_2^{out}(t). \quad (9)$$

where  $P_i^{in}$  (kW) is the power flow entering node  $i$ , and  $P_i^{out}$  (kW) is the power flow exiting node  $i$ , for  $i = 1, 2$ . As EVs consume energy by traveling, the power exiting one node is not the same as the power entering the other. The power losses in each link are defined as

$$\Delta P_{1,2} = P_1^{out} - P_2^{in} \quad , \quad \Delta P_{2,1} = P_2^{out} - P_1^{in}. \quad (10)$$

The relation between the power flows, power losses and energy are visualized in Fig. 2.

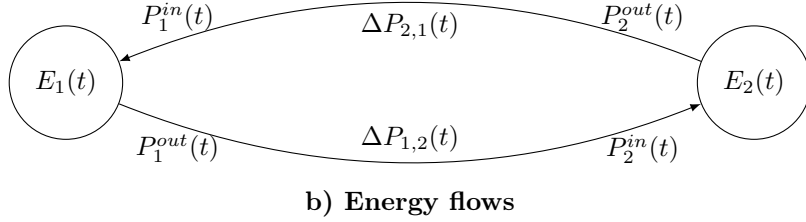


Figure 2: Energy balance between origin and destination.

The power flow leaving each node can be described in terms of the vehicle flow and state of charge,

$$P_1^{out}(t) = C\phi_{1,2}^{EV}(t)\varepsilon_1(t) \quad , \quad P_2^{out}(t) = C\phi_{1,2}^{EV}(t)\varepsilon_2(t). \quad (11)$$

To describe the power losses in each link, we consider first the energy lost per vehicle by traversing the link. Let  $F(v)$  be the force applied by each vehicle to maintain a constant speed  $v$  against friction, air drag, and other forces. Multiple definitions for this force can be obtained (see (Othman et al., 2019)), and a common form can be written as

$$F(v) = (\sin \theta + \mu \cos \theta)mg + \beta v + \frac{1}{2}\rho_{air}Ac_d v^2 \quad (12)$$

where the coefficients  $m$  and  $A$  are the mass and cross-sectional area of the vehicle,  $g$  is the acceleration due to gravity,  $\theta$  is the road inclination,  $\mu$  and  $c_d$  are the friction and air drag coefficients. Thus, the energy lost by each vehicle is the work done by this force during the trip length  $\ell$ , which becomes  $F(v)\ell$ . Additional terms can be added, such as to model the capacity of EVs to recover energy while going downhill. Thus, the power loss in each link is

$$\Delta P_{1,2}(t) = \phi_{1,2}^{EV}(t)F(v_1)\ell_1 \quad , \quad \Delta P_{2,1}(t) = \phi_{2,1}^{EV}(t)F(v_2)\ell_2. \quad (13)$$

Using the previous equations, the state of charge dynamics for node 1 can be expressed as

$$\dot{\varepsilon}_1(t) = \frac{\phi_{2,1}^{EV}(t)}{N_1(t)} \left( \varepsilon_2(t) - \varepsilon_1(t) - \frac{F(v_2)\ell_2}{C} \right), \quad (14)$$

and an analogous expression for the state of charge in node 2  $\varepsilon_2$  by switching the corresponding sub indices.

Note that the mobility and energy models are coupled in a cascading way: the mobility model can be run independently, and the energy model requires as inputs the population at each node and the arc flows. Although here we have focused on simplicity in a simple case with two nodes, this model can be extended for any number network size, where each node has two equations, one for the population and the other for the state of charge.

### 3 RESULTS AND DISCUSSION

To showcase the model, we consider the simple case with one origin and one destination of Figs. 1 and 2. In this scenario, vehicles go from origin to destination around 8h00, and return to their homes at 18h00. The simulation is done between 5h00 and 22h00, with a time step of 30 seconds. The initial conditions are  $N_1(0) = 100$ ,  $N_2(0) = 0$ ,  $\varepsilon_1(0) = 1$ ,  $\varepsilon_2(0) = 0$ . The battery capacity is set to  $C = 50kWh$ , and the energy losses at the arcs are set as  $F(v_1)\ell_1/C = 0.2$ , and  $F(v_2)\ell_2/C = 0.1$ . For simplicity, we consider only the movement of EVs.

The vehicle mobility is shown in Fig. 3, where the left plot shows the population  $N(t)$  of each node during each moment of the day, and the right plot shows the flow of vehicles moving in each direction according to the specified profile.

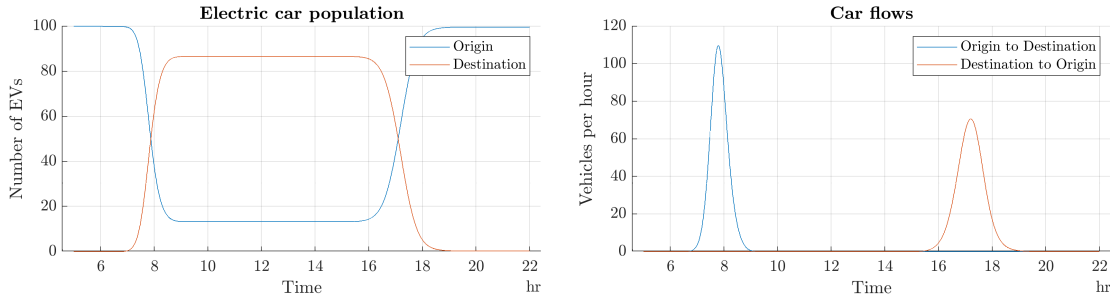


Figure 3: Mobility of electric vehicles during one day.

Figure 4 shows the energy profiles at each location during the day. The left plot shows the energy held by the EVs in each location. This is shown by the width of the corresponding colored region on the y-axis: e.g. at 6h00, all energy is in the origin node, as seen in the dark green color in Fig. 4 going from 0 to 5000 kWh. As vehicles move, the dark green area decreases while the light green area increases, as energy moves towards the destination. Some energy is lost as shown by the yellow area. At 10h00, the light green region goes from 670 to 4500 kWh, so the energy at the destination is 3830 kWh. Finally, after the vehicles come back to their origin, no more energy is stored in the light green region, and the energy has either return to the dark green region or has been lost in transit.

The plot on the right of Fig. 4, shows the available storage of EVs, calculated as  $CN_i(t)(1-\varepsilon_i(t))$ . This can be interpreted as how much energy is needed to fill the battery of all EVs in each location

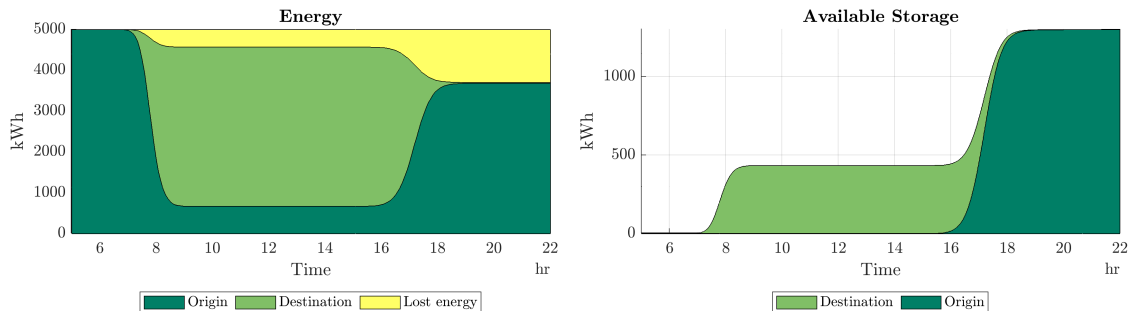


Figure 4: Energy consumption of EVs during one day.

to 100%. Thus, at 6h00 there is no available storage as all vehicles are at 100%. As move to the destination, there is some storage as energy has been depleted. However, there is available storage at the origin as the vehicles that remained are still at 100%. Finally, at the end of the day, all available storage is at the origin.

## 4 CONCLUSIONS AND PERSPECTIVES

In this work, we have introduced a new model for the mobility and energy consumption of electric vehicles in the case of urban networks. This model takes into account the mobility patterns of people going to different destination categories, multiple modes of transport, and the energy losses in transport by the EVs. The model was exemplified using a simple network of one origin and one destination. This type of model is required to study the number, location, and power definition of charging stations, as well as to understand the possible space-and-time-dependent effect of EVs in the power network.

For future work, we are currently working on the coupling with a charging station model, and the parameter estimation for more complex networks such as the case of the city of Grenoble, France. This will be used to study the effect of varying penetration rates of EVs in the city, and their effect on the power infrastructure.

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## References

- Bouscasse, H., Joly, I., & Peyhardi, J. (2019). A new family of qualitative choice models: An application of reference models to travel mode choice. *Transportation Research Part B: Methodological*, 121, 74–91. Retrieved from <https://doi.org/10.1016/j.trb.2018.12.010>
- Mondal, A., & Bhat, C. R. (2022). A spatial rank-ordered probit model with an application to travel mode choice. *Transportation Research Part B: Methodological*, 155 (August 2021), 374–393. Retrieved from <https://doi.org/10.1016/j.trb.2021.12.008>
- Niazi, M. U. B., Canudas-de Wit, C., Kibangou, A., & Bliman, P.-A. (2021, 12). Optimal Control of Urban Human Mobility for Epidemic Mitigation. In *2021 60th IEEE conference on decision and control (cdc)* (pp. 6958–6963). IEEE. Retrieved from <https://ieeexplore.ieee.org/document/9683343/>
- Othman, B., De Nunzio, G., Di Domenico, D., & Canudas-de Wit, C. (2019). Ecological traffic management: A review of the modeling and control strategies for improving environmental sustainability of road transportation. *Annual Reviews in Control*, 48, 292–311. Retrieved from <https://doi.org/10.1016/j.arcontrol.2019.09.003>
- Pratap, U., Canudas-de wit, C., & Garin, F. (2022). *Where, when and how people move in large-scale urban networks : the Grenoble saga* (Tech. Rep.). Univ. Grenoble Alpes, CNRS, INRIA, Grenoble INP, Gipsa-lab. Retrieved from <https://hal.archives-ouvertes.fr/hal-03554612>