Cooperative Control and Smart Procurement Of Naturally Generated Energy (SPONGE) for PHEV's

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***Abstract*—Electric vehicles can potentially be the best means of transportation for improving air quality, provided that they are powered by electricity from natural gas or wind, water or solar power. In this paper we describe a simple cooperative algorithm that exploits the energy management units of Plug-in Hybrid Electric Vehicles (PHEVs) to absorb the expected forthcoming energy available from renewable sources. The proposed approach bridges the gap between mobility patterns and power grid constraints, and allows to prevent green energy from being wasted while at the same time reducing the complexity burden of the power grid to charge unexpected loads of electric vehicles. Simulation results are given to show the efficacy of the proposed method.**

I. Introduction

The increasing electrification of the transportation fleet is opening previously unexplored possibilities for a synergistic collaboration between hitherto disconnected fields of the electric power grid, i.e., the *smart grid*, and the intelligent transportation network to achieve a system-level integrated optimisation.

Electric Vehicles (EVs) and Plug-in Hybrid Vehicles (PHEVs) have been seen by the power grid community as a potential threat to the power grid, since accommodating a not-fully predictable large load could ultimately cause thermal overload of some network components, low voltages at sensitive locations of the network and increase the chances of phase unbalances, see [1], [2] and [3]. At the same time, the potential of EVs and PHEVs to provide ancillary services to the grid (e.g., Vehicle-to-Grid (V2G) applications) were investigated in [4], [5], [6] and [7]. Finally, references [8], [9] and [10] investigate optimal charging of electric vehicle in the presence of intermittent power generation from renewable energy sources (e.g., solar and wind).

Note that most of the related literature, including the previous references, tend to consider separately the transportation viewpoint and the power grid one. This is due to the fact that the mobility needs of PHEV owners and the requirements of the power grid are obviously decoupled. On the other hand, in this work we take a completely different point of view, and formulate an optimisation problem that jointly takes into account both mobility patterns and also the concerns of the power grid, as better explained in the following section.

A. Contribution

The main contribution of this paper is to propose and evaluate a completely new paradigm to control the way in which hybrid vehicles discharge and recharge their batteries.

In particular, we propose that a central management service orchestrates the mode in which PHEVs travel, i.e., between the Internal Combustion Engine (ICE) and the Electric Mode (EM). In this way, it is possible to control the depletion of the batteries of a fleet of a PHEVs, and make it equal to any pre-specified quantity. Accordingly, the power grid can know, and decide, in advance the amount of the load required by the fleet of PHEVs. In particular, we control the depletion of the batteries of single vehicles in order to minimise an overall utility function that takes into account the cost of recharging the PHEVs, and in doing so encourages the use of energy generated from renewable sources for battery charging. The proposed framework allows us to achieve the following two main objectives:

- We use weather forecasts to predict the expected energy available from renewable sources, e.g., in the next 24 hours. Then, we make the PHEVs travel in EV mode for enough time to deplete their batteries in order to accommodate for the energy available from natural sources. In this way we prevent naturally generated energy from being wasted due to the absence of a consistent electrical load, or of alternative storage systems;
- In principle, it allows the smart grid to decide in advance (e.g., a day-ahead) the amount of energy that will be required to fully recharge the PHEVs, given that the battery discharge is controlled in a centralised fashion.

II. Controlling the travel mode of a hybrid vehicle

Based on the mechanical architecture, PHEVs can be classified into three categories: parallel hybrids, series hybrids, and power-split hybrids. In the parallel configuration, both the engine and the electrical motor can individually or collaboratively drive the vehicle. In the series case, a single motor is used to drive the wheels, and it can be either supplied by a battery, or by a generator transforming the engine power into electrical power, or both. Finally, the power-split hybrids use a power-split mechanism (e.g., a planetary gear) to combine the two previous configurations. Examples of papers describing the modeling and the management strategies to drive PHEVs can be found in [11], [12], [13] and [14]. Despite several techniques have been developed to optimally manage the switching between the ICE and the electric mode, or the proportion of torque provided by each of the two units, usually the following criteria are used as hard constraints (see [12]):

1) The State of Charge (SOC) of the battery should never drop under a certain threshold (i.e., to avoid endangering the lifetime of the battery);
2) The driver input (accelerating and braking pedals) should be consistently executed, unless it conflicts with the first restriction;
3) The overall energy efficiency and emission levels should be optimised, as long as the first and the second constraints are not violated.

At the same time, another common practice is to decompose the load power (which generally varies in a random fashion during real operations due to accelerations, decelerations, and climbing up and down grades) into a steady (average) power, and into a dynamic power with a zero average (see for instance [11]). Then, the common strategy is to use the ICE to supply the average power (with the advantage that it is possible to optimally configure the ICE to work very close to its most efficient working point), and the electric motor to supply the dynamic power. In this way, the total energy output from the dynamic powertrain is zero (on average) at the end of each driving cycle.

Some commercial vehicles do not allow the driver to bypass the existing Energy Management Unit (EMU) to override the optimally configured mechanism to switch between the two modes. However, manual switches are convenient for a number of reasons, e.g., to drive in some sensitive spots of a city in electric mode to avoid excessive pollution, as in the so-called *umweltzonen*[1] in Germany. Finally, refer to [15] as a practical example where the driving mode of a Toyota Prius had been remotely operated to control (via a Smartphone app) where to emit pollution due to ICE driving mode. In this paper, we use the same approach of ([15]) to switch the driving mode of a hybrid vehicle, but the goal is now to monitor the depletion of the battery to match the expected energy generated from renewable sources.

[1] http://gis.uba.de/website/umweltzonen/umweltzonen.php

A. Analogies with Demand Side Management techniques

Our main idea here is to encourage the use of PHEVs in electric mode when it is expected that energy from renewable sources will be available soon. Note that similar ideas have been already applied to other smart electric domestic appliances (e.g., washing machines, tumble driers, dishwashers) in the context of so called "Demand Side Management" (DSM) techniques. In this case, controllable loads (i.e., loads that do not need to be operated with hard time constraints) are postponed to match favourable time slots, e.g., when PhotoVoltaic (PV) roof panels provide electrical supply, see for instance [16].

In this way, locally low-cost generated energy is prioritised over more expensive, possibly less environmentally friendly energy bought from the outer electrical grid. From this perspective, our approach extends typical DSM practices to the transportation field.

III. The SPONGE paradigm

A. Smart Procurement of Energy: SPONGE

Let us now denote the electric energy dissipated by the i'th vehicle by $D_i(k)$. Our objective is to ensure that

$$\sum_{i=1}^{N} D_i(k) \geq E_{av}(k+1), \qquad (1)$$

where $E_{av}(k+1)$ is the expected energy that will be available in the next $k+1$ interval of time. For instance, during the k'th day the fleet acts like a sponge and makes available *at least* enough space to absorb the available energy that is expected during the next charging period. As stated, the problem is essentially a regulation problem that is depicted in Figure 1. Under ideal circumstances, a central authority computes the desired electrical energy consumption, and then broadcasts some signal which is received by the EMUs of the vehicles to orchestrate the switching between EV and ICE mode, so as to satisfy the regulation constraint. For instance, the signal can be the probability to travel in EV mode rather than in ICE mode, or can be the proportion of the traction torque that should be provided by the EV engine rather than from the ICE engine. We shall denote the problem expressed by Equation 1 as the basic SPONGE problem.

B. Smart Procurement of Energy: Exact SPONGE

In some cases, the objective can be to make PHEVs travel in EV mode until they deplete their batteries in order to *exactly* match the expected energy that will be available from renewable sources. We shall denote this problem as "exact SPONGE", and its mathematical formulation is as follows:

$$\sum_{i=1}^{N} D_i(k) = E_{av}(k+1). \qquad (2)$$

The main advantage of the exact SPONGE approach is that when the fleet of vehicle connect to the grid for recharging, the quantity of required energy is already known in advance (i.e.,

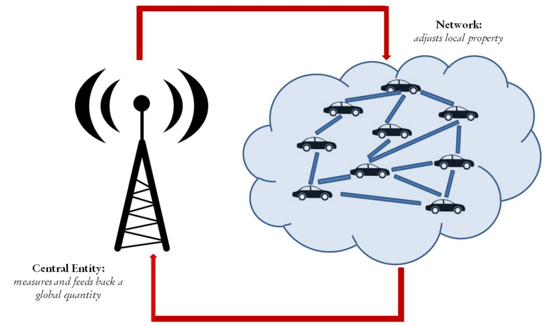

Fig. 1. Feedback loop for energy dissipation problem

it is equal to the expected energy available from renewable sources).

C. Optimised access: Optimal SPONGE

In some situations, certain vehicles may have prioritised access to the oncoming energy $E_{av}(k+1)$ via some utility function $f_i(D_i(k))$. Thus, the above problem can be reformulated in an optimisation framework as:

$$\begin{cases} \begin{array}{cc} \text{maximise} \\ \text{(or minimise)} & \sum_{i=1}^{N} f_i(D_i(k)) \\ \\ \text{subject to} & \sum_{i=1}^{N} D_i(k) = E_{av}(k+1). \end{array} \end{cases} \tag{3}$$

This optimisation may be solved in many ways under suitable assumptions on the $f_i(D_i(k))$. The problem is most interesting when the the $f_i^{\prime}s$ represent a generalised notion of utility (in which case the interest in Equation (3) is in maximisation) or a price that the i'th car pays (in which case one is interested in minimising the sum of utility functions) and is considered to be private information, not to be revealed to the utility or to other vehicles. The problem is then to solve the utility optimisation problem in a privacy preserving manner. Note that the $f_i^{\prime}s$ may be incorporated to represent various use cases. Some interesting examples include the following.

(i) For example, Original Equipment Manufacturers (OEM's) may partner with utilities to provide a service where the price of energy is part of PHEV's owners car purchase plans. Those paying more upfront, may have prioritised access to 'free energy' as it becomes available.

(ii) The f_i's could represent the price paid by an individual vehicle owner for energy access.

(iii) Or, they could be used to penalise vehicles with a lower load factor (fewer passengers).

(iv) They could be used to penalise vehicles that drive close to schools, hospitals, etc.

(v) Another interesting scenario is as follows. Some hybrid modes blend the EV motor with the ICE to optimise fuel economy/emissions. An interesting embodiment of the optimisation scenario is to take the required energy in a manner that minimises the impact on fuel economy of the fleet.

With regard to the SPONGE formulation several comments are appropriate.

Comment 1: Note that the SPONGE solution has the potential to completely revolutionise the "charging paradigm". Hitherto, most charging research has focussed on how to share the available energy among the connected fleet of vehicles in a manner that is compliant with the desires of the EV owners, the constraints of the grid, and the available power. Note that in this case, there might arise some problems in the power grid to accept the unexpected load, with the ultimate possibility of causing thermal overload of network components, low voltages at sensitive locations of the network, and increased phase unbalance ([3]). Even ignoring this, the required optimisations often place severe constraints on the EV owners in the form of inconvenient charging profiles. On the other hand, in the solution of Problem (2), one would compute the same quantity in advance, and deplete the batteries of the vehicles while travelling of the same quantity. Thus, the charging process becomes fully schedulable and programmable. The charging problem can be reduced to a best-effort problem where the cars share the available energy during the charging period using some simple algorithm such as Additive Increase Multiplicative Decrease (AIMD) algorithms ([6], [17]). Thus, clearly, the difficulties of matching the demand and the offer are shifted to the driving stage through an optimal orchestration of the ICE and EV engines.

Comment 2: The discerning reader may ask why the individual vehicle owners should not simply expend the electric energy completely before switching to ICE mode. There are many reasons for doing this. First, in some engines, electrical power and ICE are combined to reduce overall consumption, or for other objectives of interest (e.g., extend the lifetime of the battery, as in [18]). Thus, it is advantageous to keep a store of naturally generated electrical energy for this purpose. Second, access to certain parts of the city may be restricted to zero emission vehicles, see for instance the aforementioned *umweltzonen* in Germany. Thus, maintaining a store of electrical energy for this purpose is also advantageous. Finally, depleting the battery beyond the energy levels available during the next charging period, may lead to a situation where the battery is not filled during the $k+1$'th charging period. Thereby, the ICE may need to be engaged prematurely in driving, thus leading to unnecessary emissions and increased fuel consumption.

Comment 3: Note that in some cases, depending on the number of vehicles on the road, the previous optimisation problems might not have a feasible solution. For instance, in the particular case that there are no vehicles on the road, then obviously the PHEVs can not deplete their batteries to make room for the forthcoming energy. In such cases where the problem does not have a feasible solution, we will be interested in a 'best-effort' solution, where the closest feasible solution is achieved instead, see for instance ([6]).

Comment 4: Note that the SPONGE problem as described so far naturally takes place on a day-scale. For instance, vehicles are scheduled to spend a given quantity of energy during the day, and are then recharged at night time, when idle, to refill the batteries. However, in a practical scenario, it is more convenient to continuously match the energy over several time windows during the day. This has a number of benefits: if the match occurs on a day-scale, it could occur that the condition (2) is already satisfied after a few hours. Then, the cars travelling later in the day (e.g., in the afternoon) are automatically excluded from the programme because the SPONGE condition is already satisfied. On the other hand, if we split the matching problem in several windows of time, then every single car, travelling at any time, can be equally involved in the programme. Also, as soon as a new time window starts, then the matching problem can be adjusted taking into account new weather forecasts, if available, and whether the optimisation problem was feasible or not in the previous time window. Accordingly, from now on k refers to a shorter time window than a whole day, e.g., one minute.

IV. AIMD Algorithm

The most interesting scenario is the third one illustrated in Section III-C, as the others can be seen as a special case where all utility functions are the same for all vehicles. Section III-C lists a number of candidate utility functions to represent the convenience (or the inconvenience) of the owners in travelling in a given mode. For the sake of simplicity, we assume from now on that the utility functions are convex functions that represent the inconvenience of owners in travelling in EV mode, and that they can be represented by equations $f_i(\overline{D}_i(k))$, where $\overline{D}_i(k)$ represents the average energy consumed in a unit of time by the i'th vehicle, until time step k. Accordingly, the relationship between $D_i(k)$ and $\overline{D}_i(k)$ is

$$D_i(k) = \overline{D}_i(k) \cdot T_i(k), \tag{4}$$

where $T_i(k)$ is the total amount of time that the vehicle has spent travelling (in any mode) until time step k. Also, other utility functions can be used as well, as already remarked in Section III-C. Finally, a similar discussion can be made in terms of discomfort of travelling in ICE mode.

Such an optimal SPONGE scenario allows the central infrastructure to explicitly take into account personal needs of PHEVs' owners and there are many ways to solve the mathematical problem that arises. In this paper, we formulate the optimisation problem as a regulation problem with constraints, and we adopt an AIMD-like algorithm to solve it ([15], [19]). The main advantage of such an approach is that it can be implemented in a truly distributed manner (i.e., without requiring information exchange among the PHEVs), with moderate communication requirements.

The AIMD algorithm can be formulated as follows:

if $\sum_{i=1}^{N} D_i(k) < E_{av}(k+1)$
then $p_i^{EV}(k+1) = \min\left\{p_i^{EV}(k) + \alpha, 1\right\}, \forall i = 1, ..., N$
elseif $\sum_{i=1}^{N} D_i(k) \geq E_{av}(k+1)$
then *with probability* $prob_i^{EV}$
$p_i^{EV}(k+1) = \beta p_i^{EV}(k), \forall i = 1, ..., N$
or with probability $1 - prob_i^{EV}$
$p_i^{EV}(k+1) = \min\left\{p_i^{EV}(k) + \alpha, 1\right\}, \forall i = 1, ..., N$

The rationale of the algorithm is the following: some central entity computes how much space should be made available from the virtual battery of the set of vehicles at each time step $k+1$, in order to match the expected available energy from renewable sources at the end of the travelling stage (e.g., at the end of the day). If the actually available space is smaller than the desired one, then each PHEV increases its probability p_i^{EV} of travelling in EV mode (or alternatively, the proportion of torque provided by the electric engine) additively by a quantity α. If the actually available space is bigger than the desired one at the same time step (such an event is often denoted as congestion event), then the vehicles decrease their probability to travel in EV mode by a multiplicative factor $\beta < 1$ with probability $prob_i^{EV}$, or keep increasing the probability of travelling in EV mode with probability $1 - prob_i^{EV}$. Since at every time step k either an Additive Increase or a Multiplicative Decrease step is performed, these algorithms are denoted as AIMD [20]. It can be proved that if all vehicles have the same parameters α, β and $prob_i^{EV}$, then the SPONGE problem is solved by assigning the same probability (on average) to travel in EV mode to all vehicles. On the other hand, as proved in [19], by giving a different probability

$$prob_i^{EV} = \gamma \frac{\partial f(\overline{D}_i(k))/\partial \overline{D}_i(k)}{\overline{D}_i(k)}, \forall i = 1, ..., N, \tag{5}$$

then the solution of the optimal SPONGE problem is achieved, provided that the utility functions $f_i(\cdot)$ have particular properties (e.g., they are concave is one is interested in maximising their sum, or they are convex if one is interested in minimising their sum, as in the case of interest here). Equation (5) simply states that the probability to back-off at a congestion event should be proportional to $f_i'(\overline{D}_i(k))/\overline{D}_i(k)$, and γ is the proportionality factor required to map the ratio into a probability. Reference ([19]) also shows that achieving the optimal solution corresponds to achieving a consensus on the values of the derivatives of the single utility functions. Note that in order to apply the proposed AIMD method, the vehicles only need to know their own utility functions $f_i(\cdot)$, and communication requirements are limited to a broadcast from the central agent when $\sum_{i=1}^{N} D_i(k) \geq E_{av}(k+1)$ and a back-off step is required (i.e., no need of Vehicle-to-Vehicle communication). An application of the proposed algorithm is illustrated in detail in the next Section.

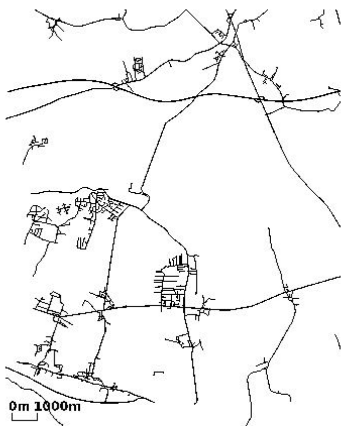

Fig. 2. Road network in the Lower Saxony area in Germany used for our simulations, extracted from Open Street Map.

V. Simulations

We now present brief simulation results to show the efficacy of the proposed idea. The following simulations are performed using the popular mobility simulator SUMO ([21]) and the given TRACI interface. A map of a rural area near Hamburg, Germany, was extracted from Open Street Map to be used as the underlying street network, and is shown in Figure 2. Figure 3 shows the simulation results for the the first two algorithms. They refer to a time period of 1000 seconds (i.e., about 17 minutes). There are 4 time windows of 250 seconds each, and there are about 600 PHEVs on the road. In our simulations, we assume that vehicles that are running out of fuel, or whose battery is getting close to physical constraints (e.g., 10% of the state of charge) are automatically discarded from the SPONGE programme. The simulation refers to a very simple example, and might correspond to the case when employees go to work using their PHEV vehicles, and the infrastructure regulates the driving mode in order to meet the target of energy that will be available at the workplace to recharge the vehicles.

Simulation results referring to the third scenario (utility optimisation) are shown in Figures 3. We remind that in this scenario the exact equality between freed space and expected forthcoming energy (Figure 3.a) is achieved by assigning different probabilities to travel in EV mode to different vehicles, according to some utility functions. We assumed that the inconvenience of vehicles in travelling in EV mode could be described through a convex quadratic function $f_i(\overline{D}_i) = a_i\overline{D}_i^2 + b_i\overline{D}_i$. Parameters a_i and b_i were different for every vehicle, and in our simulation they were randomly chosen in the interval [0,1]. Thus, the objective of the optimal SPONGE is to match the expected available energy with the free space in the batteries of the vehicles, while minimising the overall inconvenience of the owners. The evolution of the utility functions of some randomly selected vehicles is shown in Figure 3.b. As already mentioned, the optimal solution of the Problem (3) can be obtained by solving a consensus problem on the derivative of the utility functions, and such a condition is verified in Figure 3.c. Finally, Figure 3.d shows that the optimal solution is obtained by giving a different probability to travel in EV mode to each vehicle. Note that in Figure 3.d the probabilities increase additively, then drop at some congestion events, giving rise to saw-tooth signals that are characteristic of the AIMD algorithms.

VI. Conclusion

In this paper we have presented a new idea that takes advantage of the ability of PHEVs to both travel in electric and in fuel mode to absorb naturally generated electrical energy in a smart manner from the grid. From a theoretical perspective, such a problem can be easily formulated and solved using well-known algorithms for sharing a task among a number of distributed agents, (e.g., AIMD algorithms as in [17], [19]). From a practical point of view, note that the technology to remotely control the driving mode is also already available, as it was developed in ([15]) for different purposes.

Our current plan is to extend the preliminary simulation results given in Section V to more realistic and large-scale examples. In parallel, we intend to start implementing the approach in a reduced number of PHEVs, as a proof-of-concept of the paper idea. We shall adapt the experimental set-up of ([15]) to the new case of interest, to remotely control the EV/ICE engine switching. The practical implementation of the algorithm will require a careful handling of possibly frequent mode switches, and averaging techniques will be used to implement them in a manner that would not endanger the life of the battery. Finally, we shall integrate a reliable weather forecast software in the overall system, in order to take optimal decisions about when to switch from one mode to another mode.

Acknowledgment

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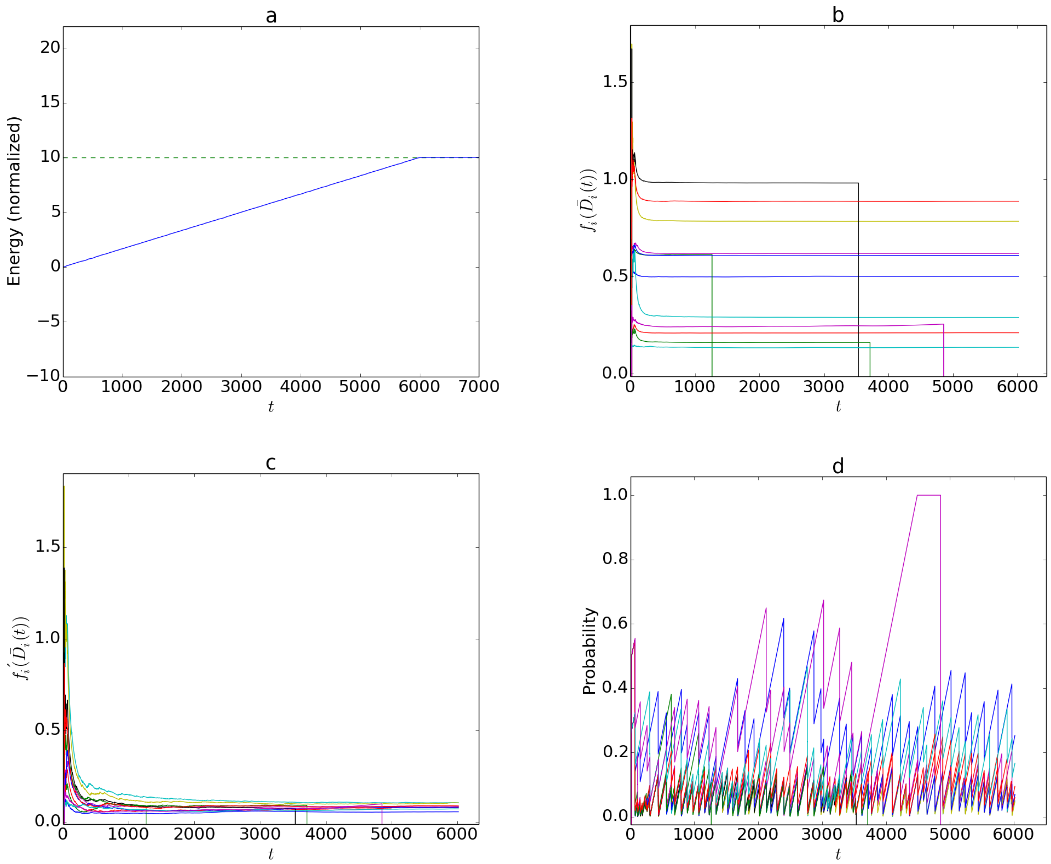

Fig. 3. Figure a shows that the overall constraint is again exactly satisfied at the end of the simulation. However, it is now achieved by minimising the sum of utility functions (single utility functions are shown in b). Figure c shows that the optimal solution has been achieved in fact, since there is a consensus on the derivative of the utility functions. Figure d emphasises that the utility optimisation problem is solved by assigning different probabilities of travelling in EV mode to different vehicles, according to their utility functions. Note that some vehicles reaching their destination before the end of the simulation exit the SPONGE programme in advance.

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