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Research Article

Smart Procurement Of Naturally Generated Energy (SPONGE) for PHEVs

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In this paper, we propose a new engine management system for hybrid vehicles to enable energy providers and car manufacturers to provide new services. Energy forecasts are used to collaboratively orchestrate the behaviour of engine management systems of a fleet of PHEVs to absorb oncoming energy in a smart manner. Cooperative algorithms are suggested to manage the energy absorption in an optimal manner for a fleet of vehicles, and the mobility simulator SUMO is used to demonstrate the efficacy of the proposed idea.

Keywords: Consensus algorithms; Plug-in Hybrid Electric Vehicles (PHEVs); Renewable energy

1 Introduction

Many factors drive problems within the automotive industry, but one of the most considerable factors is the insatiable appetite that transport has for energy. For instance, energy consumption from the transport sector of the UK in 2013 equated to 53.4 million tonnes of oil equivalent (Department of Energy & Climate Change (2014)). This sum represented a considerable 36% of the total final consumption of UK energy products in 2013 (Department of Energy & Climate Change (2014)). Moreover, 74% (i.e. 39.3 million tonnes of oil equivalent) of this energy consumption in the UK transport sector was caused by road transport alone (Department of Energy & Climate Change (2014)). Reducing the energy consumption of road traffic has thus been a major focus for investigators.

Up until now, it can be said that three levels of response towards reducing road traffic's thirst for energy have been provided by car manufacturers. The first response given was that vehicles were made to be more efficient in terms of having better engines (Khodabakhshian et al. (2014), Samoilenko et al. (2013), Yuen et al. (1986)) and improved aerodynamics (SEI (2007-2013)). This approach has resulted in limited reductions in energy consumption. R&D continues with regards to improving engine combustion efficiency, powertrain friction reduction, waste-heat recovery, vehicle rolling resistance, air drag reduction, and improved controls (Volvo (2014), California Energy Commission (2002-2015)).

As a second level of response, efforts have been made to teach people how to drive their vehicles more efficiently. Examples include the ECOWILL project that ran from March 2010 to April 2013, funded by the Intelligent Energy Europe programme of the European Union, which

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aimed to boost and train people across thirteen countries in Europe in ecodriving (ECOWILL (2010)). Many vehicles now come with ecodriving options as standard (Renault (2015)). New vehicle technologies have been widely adopted to alert drivers to more energy efficient driving practices. For instance, gear shift indicators for certain classes of vehicles were recently made mandatory within the European Union (EUROPA (2010)). The purpose of the indicators is to inform drivers of when to change gear to minimise fuel consumption. As opposed to mandatory technology installments, much optional technology and gamification to teach environmentally friendly driving behaviours also exists. For example, the project TEAM (TEAM (2012-2015)), a European research project co-funded by the European Union, will bring about, among other applications, the development of the Green, Safe and Collaborative Driving Serious Game and Community Building (SG-CB) application. The aim of this application is to create a gamified social network environment for participants (drivers and travellers) to be able to exchange simple feedback about their current level of performance and thus build a community and together reach higher levels of green driving and lower traffic. Efforts have also been made to encourage carsharing (CarSharing.ie (2015), GoCar (2008-2015)). According to The Economist (2014), carsharing can reduce car ownership at a rate of one rental car replacing fifteen owned vehicles by some estimates.

The third level of response offered towards reducing vehicular energy consumption concerns the emergence of collaborative and connected vehicle technology. For example, see Liu et al. (2015a), where a distributed and privacy-aware speed advisory system was proposed in which the objective was to recommend optimal speeds for groups of vehicles travelling along highways to minimise emissions over the entire fleet. In Liu et al. (2015b), an approach was proposed that simultaneously optimised the numbers and locations of, and speed limits posted on, variable message signs as a means to improve the smoothness and reduce the environmental impact of freeway traffic. The model provided in Liu et al. (2015b) was categorised as a mixed-integer nonlinear programming problem and solved using genetic algorithms. Future intended improvements include the ability to incorporate real-time traffic data. In Helbing et al. (1998), a type of observed collective behaviour regarding diverse sets of vehicles travelling along a two-lane highway with different velocities was described.

Now, in our current work, we take a more holistic view of the energy consumption process and introduce a fourth level of response. Specifically, we wish to allow drivers to make use of free renewable energy as it becomes available. We do that by allowing weather forecasts to influence the energy management system of vehicles individually and fleet-wise. This provides us with the advantage of using free renewable energy in an optimal way to maximise the efficiency of the transportation fleet. We call this idea Smart Procurement Of Naturally Generated Energy (SPONGE). As we will see, SPONGE can indeed be viewed as an evolution of ecodriving, where we now prime cars to use renewables as they become available, thus following a "use it or lose it" line of thought.

In addition, this approach is also consistent with a general trend to increase the utilisation of renewable energy as part of the general transportation system. Several countries have already started producing a large fraction of electrical power from renewable sources. For example, wind alone provided more than 30% of electricity production in Denmark in 2012, and is foreseen to supply 50% of the overall demand by the year 2020 (Marinelli et al. (2014)). Further, Denmark's stated goal goes beyond this objective with an aspiration to become 100% renewable by 2050 (Meibom et al. 2013), with similar aspirations being held in many other countries. The merits of using renewables is the cleanness of the energy supply and the associated benefits for both greenhouse gas emissions and air quality. A significant impediment to the integration of renewables into the grid is the need for new demand side management practices to match power generation with power consumption (Bičík et al. (2012), Al Faruque (2014)) on a daily basis.

Despite the increasing quantity of energy that is produced from renewable sources, and despite the many efforts to encourage consumers to shift loads to times of the day when renewable energy is available, there is still a significant mismatch between renewable energy availability and energy demand, and conventional power plants (e.g. coal or gas-fired power plants) are still widely used to back up energy generation. The necessity to use conventional power plants is not convenient in terms of economic costs (i.e. fuel and carbon costs have to be taken into account) and in terms of existing and anticipated environmental regulations (e.g. emissions of CO_2, NOx or other pollutants). With this in mind, a number of strategies have been proposed to deal with supply-demand imbalance. First, storage systems represent an attractive possibility to alleviate the requirement of continuous matching between energy demand and offer; see the Economist Technology Quarterly (December 2014) for a recent discussion of advances in this direction (The Economist (2014)). Roughly speaking, energy generated from renewable sources can be stored when availability exceeds the energy demand (e.g. eolic energy at night time), and can be released as needed as an alternative to switching on a conventional power plant. Amongst the available storage systems, the ability of Electric Vehicles (EVs) to act as an 'aggregated' battery for such purposes has been given as one of the most important arguments in favour of EV adoption as a mode of automotive mobility. To further elaborate, in the event of a high level of adoption of electric vehicles, a large virtual battery system would be automatically available without requirements of big investment in other storage devices (Liu et al. (2013), Tushar et al. (2014) and Stüdli et al. (2014)). Such a possibility would be convenient also from the EV side, as many studies show that EVs represent a viable solution to limit emissions particularly if they are charged from energy coming from renewable sources (Tessum et al. (2014)). Despite the apparent suitability of EVs to provide battery storage, some studies have shown that the use of EVs in this manner is not without problems. Their use as storage devices is currently quite limited due to low penetration levels, and due to the fact that, usually, only a small proportion of the EVs' battery capacity is available for energy exchange Ancillotti et al. (2014) (the main reason for this is that EV owners are primarily concerned on having enough battery for their next trip (Stüdli et al. (2014))). A further complication arises due to the fact that renewable energy is, by its very nature, uncertain. Thus, supplying the EV fleet with the required energy needed for mobility creates the need for complicated optimisation and scheduling algorithms (and infrastructure) on the supply side, places contractual requirements on generators of electricity, and requires EV owners to plug in their vehicles at certain times of the day[1]. Thus, a second strategy in dealing with the intermittent nature of the supply of naturally generated energy is to make devices smarter. That is, they should be context aware, and change their behaviours in a manner that enables them to utilise renewable energy when it becomes available. Clearly, in the case of EVs, this is not possible since there is a very natural decoupling of the mobility needs of EV owners and the available supply of energy from renewable sources. That is, the grid should always serve the mobility needs of users as a primary objective. However, in the case of plug-in hybrid vehicles (PHEVs), there are two power sources for each vehicle. Thus, vehicle owners have a choice at every instant of time as to whether the PHEV's electric engine is utilised, the Internal Combustion Engine (ICE), or both. Thus, a second advantage of the work presented in this paper is to exploit such a flexibility to couple the needs of the grid with those of the vehicle owner, and to show how this offers the potential for a truly smart integration of vehicles into the energy grid, as described in the following paragraph.

1.1 *Paper contribution*

The contribution of this paper is to propose a novel engine management unit (EMU) for PHEVs. The EMU orchestrates between the use of the electrical engine and that of the ICE in order to

[1]Electricity Demand and Supply Harmonisation for Electric Vehicles, available online at `http://edash.eu` [last checked, April 2015]

prioritise energy charging from renewable sources over other conventional energy sources. As a consequence, it becomes possible to use a network of PHEVs as an "energy sponge" and to prime them to capture renewable energy as it becomes available (from now on, we shall refer to such an idea as "SPONGE"). For this purpose, weather forecast services can be used to make predictions of how much energy will be available from solar/wind power plants in the near future (e.g. the next 24 hours). Based on such forecasts, elementary cooperative strategies can be implemented in a manner that is transparent to users, to make space in a fleet of vehicles (i.e. in their batteries) for the forthcoming energy. Essentially, vehicle owners allow the EMU (engine management unit) of the vehicle to be remotely controlled by a centralised management service that matches the expected forthcoming energy from renewable sources with the free battery space in the fleet of PHEVs. By doing this, users fully utilise the available clean energy as it becomes available (possibly at zero financial cost if coming from private roof top solar panels or from a self-owned wind source), prevent clean energy from being wasted by ensuring that there is always enough capacity available for storage, and help balance energy supply and demand through active scheduling of energy sourcing for vehicles in a pro-active manner. As a side effect, we shall also see that this strategy has the potential to significantly reduce the complexity burden of charging these vehicles by enabling best-effort charging algorithms to be deployed.

This paper is an extended version of the idea presented at a Workshop at Yale University Häusler et al. (2015b) and preliminary described in Häusler et al. (2015a). Specifically, this paper presents a more detailed description of the basic algorithm, further introduces more advanced variants of the algorithm, and provides more extended simulation results.

The work presented here complements existing work in the context of optimised charging of EVs (Stüdli et al. (2014)) and in developing context-aware cooperative control strategies for hybrid vehicles (Schlote et al. (2014)). From a technological perspective, the work most resembles strategies to regulate pollution that have already been implemented in practice and described in (Schlote et al. (2014)). However, the goals of the current problem statement differ significantly from the aforementioned work, and open, we believe, significant market opportunities by presenting mobility and energy products in a truly integrated manner.

This paper is organised as follows. The next section states the basic SPONGE problem, and some alternative formulations, in a more formal fashion. Section 3 describes various methods that can be used to implement the SPONGE approach in practice. Section 4 provides some simulation results to support the efficacy of the proposed methods. Finally, in Section 5, we summarise our findings and outline our current lines of research in this topic.

2 Problem statement and Assumptions

For convenience, and ease of exposition, we make the following set of simplistic assumptions.

(i) We discretise every k'th day (a 24 hour day) into T same time clock periods, each of length ΔT. We assume that for some fixed period during the day, these vehicles are plugged in, and that for this period, a reliable day-ahead forecast of available renewable energy is available. We denote this available energy by $E_{av}(k+1)$. For example, a typical assumption might be that the vehicles charge from 11pm to 6am, though it is not necessary for this time period to be the same for all vehicles. Although, in principle, the future horizon of optimisation can be longer than one day, weather forecasts might not be reliable enough to support optimal decisions over longer time periods, see (Hodge et al. (2012) and Zhang et al. (2013)).

(ii) We assume that during some other fixed time period of the day (e.g., 9am to 6pm), a group of plug-in hybrid vehicles, with maximum number of N, will participate in a scheme to proactively adjust their energy consumption patterns at every available clock period so as to make available space in the electric vehicle battery. We assume that this fixed time period consists of M clock periods and we index every available clock period as $\tau \in \{1, 2, ..., M\}$.

(iii) Each vehicle is assumed to be capable of operating in fully EV mode, in ICE mode, or a combination of both (as in the Toyota Prius). Reference (Schlote et al. (2014)) describes how the default operation mode of a hybrid vehicle can be bypassed and reprogrammed in practice (also remotely), for the specific case of the Toyota Prius.

(iv) For the remainder of the day, we assume that at any clock period $n(\tau) \leq N$ vehicles are in transit, and that these vehicles can report their energy consumption over some period to a central agent.

2.1 *Smart Procurement of Energy: SPONGE*

Let us now denote the electric energy dissipated by the i'th vehicle at the τ'th time clock period by $D_i(\tau)$. Our objective is to ensure that

$$\sum_{\tau=1}^{M} \sum_{i=1}^{n(\tau)} D_i(\tau) \geq E_{av}(k+1), \tag{1}$$

where $\sum_{\tau=1}^{M} D_i(\tau) = D_i(k)$. The formula implies 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 in $(k+1)$'th day. 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.

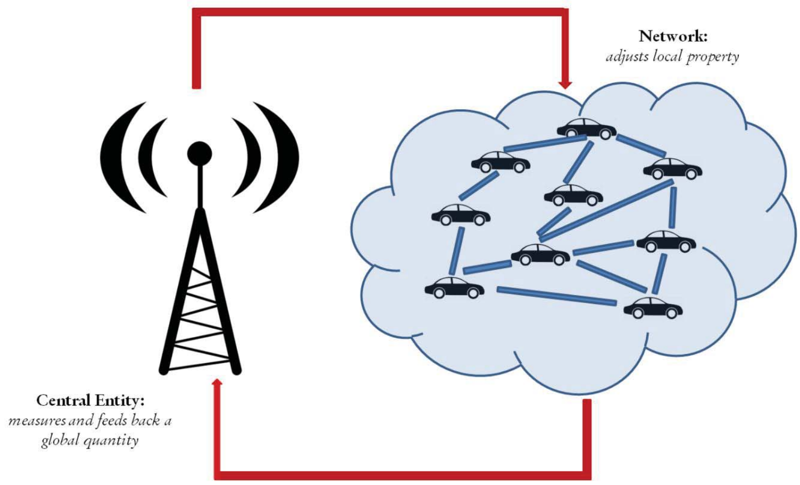

Figure 1. Feedback loop for energy dissipation problem.

2.2 *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:

$$\sum_{\tau=1}^{M} \sum_{i=1}^{n(\tau)} D_i(\tau) = E_{av}(k+1). \tag{2}$$

The main advantage of the exact SPONGE approach is that when the fleet of vehicles connect to the grid for recharging, the quantity of required energy is already known in advance (i.e., it is equal to the expected energy available from renewable sources).

2.3 *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. Thus, the above problem can be reformulated in an optimisation framework as:

$$\begin{cases} \begin{array}{c}\text{maximise}\\ \text{(or minimise)}\end{array} & \displaystyle\sum_{i=1}^{n(\tau)} f_i(\overline{D}_i(\tau)) \\ \\ \text{subject to} & \displaystyle\sum_{i=1}^{n(\tau)} \overline{D}_i(\tau) = \frac{E_{av}(k+1)}{M}. \end{cases} \tag{3}$$

where $\overline{D}_i(\tau)$ is defined as the average of energy distributed to the i'th vehicle since the vehicles began to participate in the scheme. Note also in this definition we shall consider the situation only when the available energy $\frac{E_{av}(k+1)}{M}$ at every time clock τ is completely distributed among these $n(\tau)$ vehicles. This optimisation may be solved in many ways under suitable assumptions on the f_i's. 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 (i.e., in a manner that makes it difficult for the functions f_i's to be reconstructed by a centralised authority or other users). Note that the f_i's may be incorporated to represent various use cases. Some interesting examples include the following.

(i) For example, 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 simplify the "charging paradigm". Hitherto, most charging research has focused 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 (de Hoog et al. (2015)). 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 (Stüdli et al. (2014), Crisostomi et al. (2014)). 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 Shaltout et al. (2014)). 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 so-called *umweltzonen* in Germany[1]. 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 (Stüdli et al. (2014)).

3 Methods

Clearly there are many ways in which the problems specified in the previous section may be solved, and we now describe some simple methods that can be adopted. To this end we assume that each vehicle is synchronised with a clock (possibly a multiple of a GPS clock), and reports its every consumption over the τ'th clock period as $D_i(\tau)$ to a centralised authority. This centralised authority aggregates this energy consumption and broadcasts a signal to the vehicles depending

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

on whether the aggregated consumption is smaller than $E_{av}(k+1)$ or not. The probability whether the i'th vehicle travels in fully electric mode in the $(\tau+1)$'th period depends on this broadcasted signal. In the following two *use cases* we shall see examples of signals that can be used to orchestrate the fleet behaviour. Note that in what follows we formulate Equations (1) - (3) as regulation stochastic optimisation problems. This means, for each of the problems defined in Section 2, an approximated solution is given only.

3.1 *Use case 1: Fair energy consumption*

The fair energy consumption case refers to the case when all the vehicles participating to the SPONGE program participate in the same manner; namely, they have the same probability to travel in EV mode. In the SPONGE case illustrated in Section 2.1, a simple regulator can be used:

$$\begin{aligned}&\textbf{Initialisation } (\tau = 1)\textbf{:}\; p_i^{EV}(\tau) = p_0,\; D_i(\tau) = D_0, \forall i = 1, ..., n(\tau)\\ &p_i^{EV}(\tau+1) = g_1(p_i^{EV}(\tau) + \eta_1(\tfrac{E_{av}(k+1)}{M} - \textstyle\sum_{i=1}^{n(\tau)} D_i(\tau))), \forall i = 1, ..., n(\tau), \forall \tau = 1, ..., M\end{aligned} \tag{4}$$

where p_0, D_0 and η_1 are all positive constants. In this case, at every interval of time ΔT (e.g., every minute), each vehicle is required to update its probability to travel in EV mode at the next time interval according to a piecewise function $g_1 : \mathrm{R} \mapsto [0,1]$, which is defined as:

$$g_1(p) = \begin{cases} c_i, \text{ if } & p < 0, \\ p, \text{ if } & 0 \le p \le 1, \\ 1, \text{ if } & 1 < p, \end{cases} \tag{5}$$

where c_i is a probability value in $[0,1]$ for each vehicle i. This value models that if enough space is already available, then the vehicles are still allowed to travel in EV mode with a probability c_i before their batteries are depleted. Also note that, as already anticipated, even if all $p_i^{EV}(\tau)$'s are set to 1, the goal might not be accomplished if not enough vehicles are travelling in the time interval of interest.

Comment 4: Note that the request that vehicles have to travel in EV mode with probability 0.6 can be implemented in practice either by making 60% of the vehicles travel in EV mode, or by making 60% of the traction provided by the EV engine, and the residual by the ICE engine, in every car.

As for the exact SPONGE case illustrated in Section 2.2, a similar discrete-time regulator can be adopted in the following manner:

$$\begin{aligned}&\textbf{Initialisation } (\tau = 1)\textbf{:}\; p_i^{EV}(\tau) = p_0,\; D_i(\tau) = D_0, \forall i = 1, ..., n(\tau)\\ &p_i^{EV}(\tau+1) = g_2(p_i^{EV}(\tau) + \eta_2(\tfrac{E_{av}(k+1)}{M} - \textstyle\sum_{i=1}^{n(\tau)} D_i(\tau))), \forall i = 1, ..., n(\tau), \forall \tau = 1, ..., M\end{aligned} \tag{6}$$

where η_2 is also a positive constant and g_2 is defined as:

$$g_2(p) = \begin{cases} 0, \text{ if } & p < 0, \\ p, \text{ if } & 0 \le p \le 1, \\ 1, \text{ if } & 1 < p. \end{cases} \tag{7}$$

Compared to the SPONGE case, the main difference in this case is that the control objective is to *exactly* deplete the batteries of the quantity $E_{av}(k+1)$, while vehicles are not allowed to over-deplete their batteries. Although such a solution may appear to penalise the drivers (i.e., they are forced to travel in ICE mode to avoid over-depleting their batteries), it is very convenient for the grid, as it is possible to predict in advance exactly how much energy will have to be delivered to the fleet of vehicles. Also, as already mentioned in **Comment 2**, there may be good reasons for drivers to preserve a store of electric energy.

Note that the proposed approaches can be used to tackle many practical scenarios of interest. For instance, we can assume that a company provides a free battery-charging service to the PHEVs of the employees whenever there is enough power generated from some connected solar/wind plants in the surroundings of the company buildings. Then, there should always be some battery available for recharging whenever there is available energy from natural sources. Then, the employees collaborate to equally make space in their batteries to absorb the forthcoming energy. However note that, although such a scenario gives rise to fair solutions, still personal constraints of single employees are not taken into account. In this perspective, the scenario can be made more complicated (and more customisable) as described in the following subsection.

3.2 *Use case 2: Utility optimisation*

The third scenario illustrated in Section 2.3 is different from the previous two, since different probabilities should be computed for different users, taking personal constraints into account. Section 2.3 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 $f_i(\overline{D}_i(\tau))$, where $\overline{D}_i(\tau)$ represents the average energy consumed, when current available energy is fully distributed, in a unit of time by the i'th vehicle, until time step τ. Also, other utility functions can be used as well, as already remarked in Section 2.3. 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 (Schlote et al. (2014), Wirth et al. (2015)). The main advantage of such an approach is that it only requires binary feedback from the infrastructure.

The AIMD algorithm can be formulated as follows:

$$
\begin{array}{ll}
\textbf{if} & \sum_{h=1}^{\tau}\sum_{i=1}^{n(h)} D_i(h) < \frac{E_{av}(k+1)}{M}\cdot\tau \\
\textit{then} & D_i(\tau+1) = D_i(\tau)+\alpha, \forall i = 1,...,n(\tau), \forall\tau = 1,...,M \\
\textbf{elseif} & \sum_{h=1}^{\tau}\sum_{i=1}^{n(h)} D_i(h) \geq \frac{E_{av}(k+1)}{M}\cdot\tau \\
\textit{then} & \textit{with probability } prob_i^{EV}(\tau) \\
 & D_i(\tau+1) = \beta D_i(\tau), \forall i = 1,...,n(\tau), \forall\tau = 1,...,M \\
 & \textit{or with probability } 1 - prob_i^{EV}(\tau) \\
 & D_i(\tau+1) = D_i(\tau)+\alpha, \forall i = 1,...,n(\tau), \forall\tau = 1,...,M
\end{array}
$$

The rationale of the algorithm is the following: some central entity are targeting to distribute the current available energy $\frac{E_{av}(k+1)}{M}$ to the virtual battery of the set of vehicles at each time clock τ 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).

Since the current available energy is not known to all these vehicles, if sum of the $D_i(\tau)$ of all PHEVs is smaller than the desired one, then each PHEV increases its target energy consumption during the next time clock period $\tau + 1$ by a quantity α. However, if sum of the current distributed energy of all PHEVs is bigger than the desired one (we denote such a situation as a congestion event), then the vehicles decrease their target energy consumption, travelling in clock period $\tau+1$, by a multiplicative factor $\beta < 1$ with probability $prob_i^{EV}(\tau)$.

As can be shown in Wirth et al. (2015), by defining

$$prob_i^{EV}(\tau) = \gamma \frac{\partial f_i(\overline{D}_i(\tau))/\partial \overline{D}_i(\tau)}{\overline{D}_i(\tau)}, \forall i = 1, ..., n(\tau), \forall \tau = 1, ..., M \quad (8)$$

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 if 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 (8) simply states that the probability to back-off at a congestion event should be proportional to $f_i'(\overline{D}_i(\tau))/\overline{D}_i(\tau)$, and γ is the proportionality factor required to map the ratio into a probability. Reference (Wirth et al. (2015)) 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 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.

Comment 5: In some applications, for example, where vehicles have fixed routes and itineraries, it makes sense to solve Equation (3) in a batch fashion at a certain instance in time every day (e.g., early in the morning). For example, owners of bus fleets with fixed routes may wish to do this when deploying SPONGE. In such situations, it may still make sense to use a distributed algorithm to solve this batch problem (as described above). The compelling reason to do this is to preserve the privacy details of each bus, namely the f_i, when solving the optimisation problem. We should briefly mention that the algorithm described in the previous section can be adapted to do this.

4 Simulations and Discussion

In this section, we demonstrate via simulation and compare the previously described methods used to implement SPONGE. We explore their shortcomings and advantages, and discuss how these shortcomings might be improved upon. To do so, we use SUMO-based simulation to validate our methodologies. SUMO (Simulation of Urban MObility) is an open source, microscopic road traffic simulation package primarily being developed at the Institute of Transportation Systems at the German Aerospace Centre (DLR) Krajzewicz et al. (2012). SUMO is designed to handle large road networks, and comes with a "remote control" interface, TraCI (short for Traffic Control Interface) Wegener et al. (2008), that allows one to adapt the simulation and to control singular vehicles on the fly. In all of the following simulations, we shall assume that vehicles drive in the area enclosing the campus of the National University of Ireland Maynooth (NUIM), as shown in Figure 2.

Figure 2. Area near the NUIM campus, used for our simulation set-up.

4.1 *Exact SPONGE Regulation*

We first revisit the procedures demonstrated for solving the original (exact) SPONGE problems, as described in Section 2.2. As stated, this problem is regulatory in nature, the idea being to regulate fleet electric energy consumption. The kinds of signals broadcast by the central authority to orchestrate fleet behaviour are probabilistic in nature, where the probability that vehicles are directed to travel in EV mode is a function of the gap between the desired target of electric energy that the fleet should consume, and the energy that each vehicle has already consumed.

Simulation 1: We demonstrate the regulation procedure by applying it to regulate energy consumption among a group PHEVs. As in the exact SPONGE case, we assume that the objective is to achieve an overall energy consumption equal to the expected energy that will be available from renewable sources. We assume that 40 PHEVs participate to the SPONGE scheme from 9am to 6pm. The iteration step-size of the algorithm is assumed to be 1 minute, thus providing a reasonable switching time interval for each PHEV operating in either EV or ICE mode. Accordingly, the algorithm is iterated 540 times overall. Further, we assume that the total available renewable energy for the next charging period is equal to 540 kWh, so that energy should be allocated with a rate of 1kWh/minute during 9am to 6pm, to match the final target. Finally, each PHEV is assumed to have the same battery capacity of 20 kWh with initial state of charge (SOC) of the battery equal to 80%.

At every time step, each PHEV sends its current energy state to the central infrastructure. Upon receiving these data, the central infrastructure calculates and broadcasts some global signals to all PHEVs. Upon receiving this information, each PHEV updates its probability to travel in EV mode. Then, the PHEV compares such a value with its own "coin-flipped" value, which is a uniformly distributed random number in the range (0,1), and finally decides which mode (i.e. EV or ICEV) the vehicle should travel during the next time interval. Note that, we are assuming here that the electric mode of each PHEV can only have two states, i.e., either completely on (value 1) or off (ICE mode, value 0), during each unit of time (i.e. 1 minute). In the SUMO simulations, the practical energy consumption of each vehicle was calculated according to an approximated linear mapping between the travelled distance and the SOC. The simulation results are illustrated in Figures 3 - 4. In Figure 3, it is shown that the Exact SPONGE algorithm can indeed effectively regulate the energy consumption among PHEVs in order to eventually achieve the expected energy target. As a further result, Figure 4 shows that the final objective is achieved by maintaining the energy rate constant throughout the day (i.e., 1kWh/minute).

Comment 6: As a general remark, there are some shortcomings of deploying this approach in

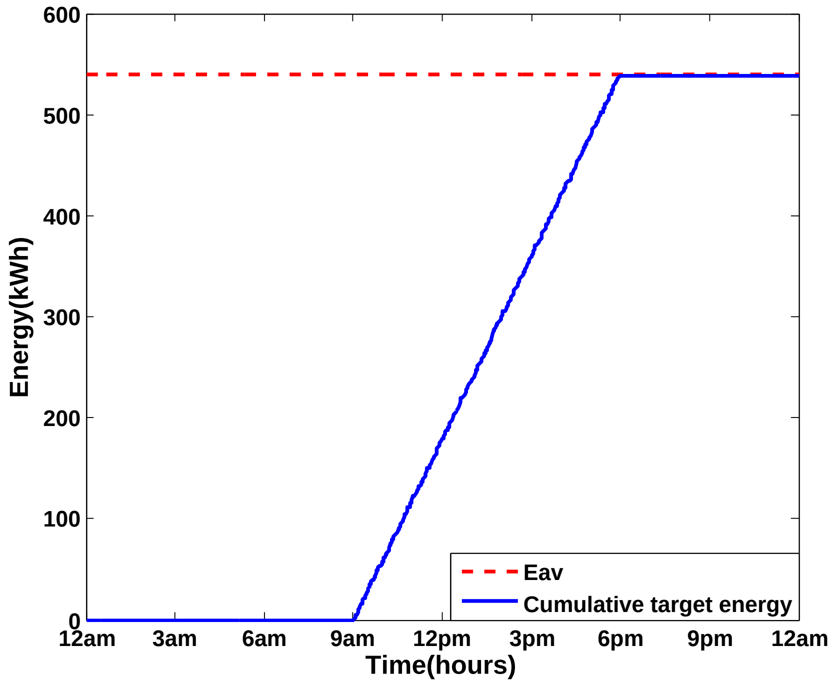

Figure 3. Evolution of the cumulative target energy allocated to the fleet of PHEVs.

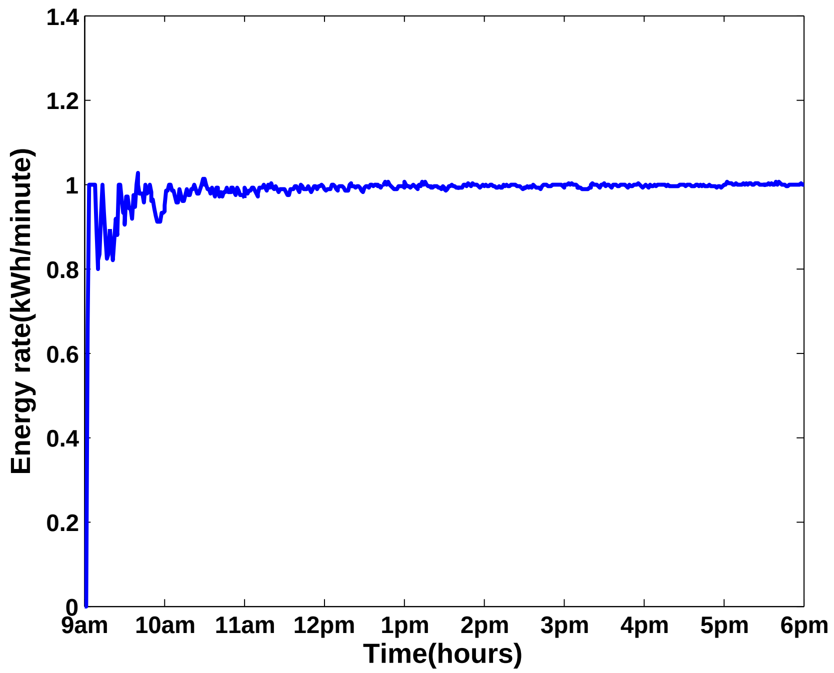

Figure 4. Evolution of the averaged allocation rate of target energy to the fleet of PHEVs.

practice, which include the following: (1) there is continuous feedback from the infrastructures to the vehicles; and (2) the gains on the control algorithm depend on the dimension on the network.

4.2 *Optimal SPONGE and AIMD*

In this simulation, we validate the procedure shown for solving the Optimal SPONGE problem, as described in Section 2.3. Recall that this setup is more refined, in that the individual requirements of certain vehicles can be taken into account in terms of prioritising access to oncoming available electric energy via the use of utility functions. As a consequence, single PHEVs will now have different probabilities to travel in EV mode. Such probabilistic signals that determine vehicular engine mode behaviour are unique to, and are computed by, each vehicle, thus taking into account personal constraints. Meanwhile, the central authority broadcasts only single bits of information regarding the occurrence of congestion events. Specifically, the optimisation problem is solved using an AIMD-like technique.

Simulation 2: Let us indeed now illustrate how to apply an AIMD-based optimisation algorithm to solve an optimal SPONGE problem. When a congestion event occurs, the central infrastructure will broadcast a one bit signal (e.g. 0) indicating all PHEVs attempt to "back-off" in terms of electric energy consumption; otherwise, it will broadcast an opposing signal (i.e. 1, in this specific case). Upon receiving the signal, each PHEV will decide to either increase or decrease its target energy for the next time interval. Specifically, when receiving the signal 0, each PHEV coin-flips a random number, and compares this number with another determined probability value, depending on the vehicle's associated utility function, to decide whether to increase or decrease its target energy. At every time step, each PHEV updates its real consumed energy and compares this value with its target energy. For convenience, it is assumed that each vehicle will automatically switch to the ICE mode whenever the real consumed energy equals the target energy.

The SUMO simulation set-up, and the assumptions on the vehicles are the same of the previous simulation. Figure 5 and Figure 6 show that the final target is successfully achieved again, also with the AIMD approach. Note that the suggested approach shows a good utilisation of the available energy (i.e., energy consumption is close to the constraint) than a synchronised AIMD algorithm, when *all* agents back-off whenever a congestion event occurs. To better evaluate the optimality of the solution, we further evaluate the long-term behaviour of the algorithm, up to 50000 consecutive congestion events. In particular, Figure 7 shows the convergence behaviour of the averaged energy consumption. Moreover, it is observed that the optimality of the algorithm is achieved when all derivatives of the utility functions converge to consensus. This is occurring in practice, as depicted in Figure 8.

AIMD has significant advantages over the previous method. First, it can be used to solve an optimisation problem. Second, only binary feedback is required from the infrastructure. Third, this feedback is intermittent. Fourth, the gain in Equation (8) is chosen to ensure that the probability is in the interval $[0, 1]$. This gain only depends on the worst case utility function and independent of network dimension. Finally, the rationale of the method is to ensure that the derivatives of the utility functions achieve consensus. In principle, any choice of function on the right hand side of Equation (8) that achieves this is a valid choice of probability function. For example, it can be seen that when f_i''s satisfy the conditions given in (Wirth et al. (2015)), then by replacing the right hand side of Equation (8) by $\frac{\kappa_1+\kappa_2 g(f_i'(\overline{D}_i))}{\overline{D}_i}$, with $k_1, k_2 > 0$ and g chosen such that the conditions in (Wirth et al. (2015)) are satisfied, then consensus of the derivative is also implied. This makes, under mild assumption (that each agent does not reveal g) the AIMD algorithm privacy-preserving.

4.3 *Extensions to SPONGE regulation*

As we have seen in the previous subsection, AIMD offers significant advantages over a simple regulator to solve the SPONGE regulation problem. However, the main drawback of AIMD is that every single PHEV should continuously monitor its own AIMD state: in fact, this is compared with a randomly extracted number to finally choose the driving mode in the minute interval. However, performing such an AIMD action does require some actuation abilities

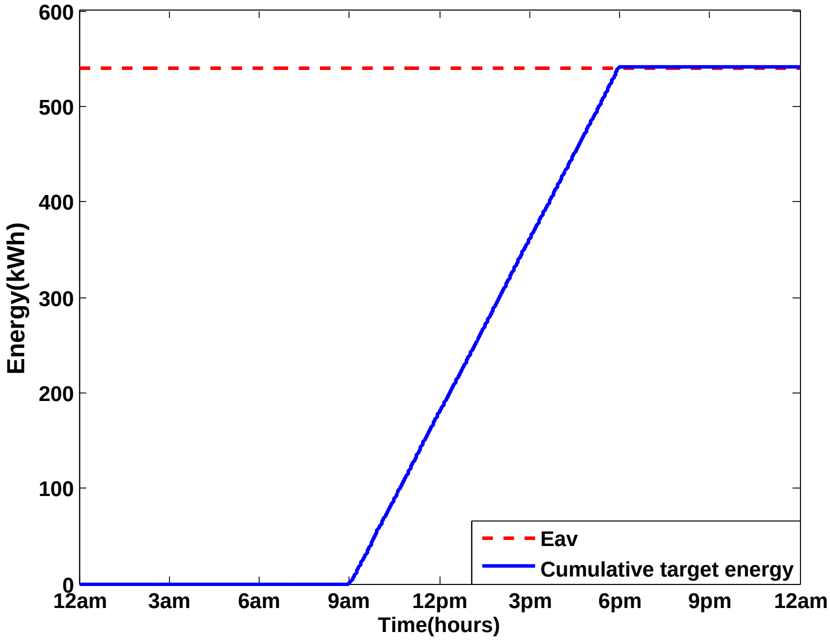

Figure 5. Evolution of the cumulative target energy allocated to the fleet of PHEVs.

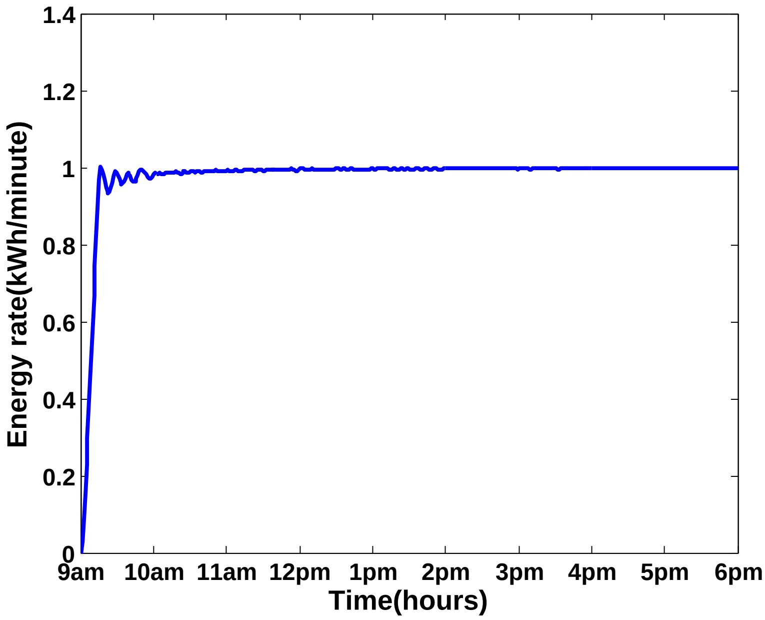

Figure 6. Evolution of the averaged allocation rate of target energy to the fleet of PHEVs.

from the side of the PHEV. In the remainder of this section, we shall see how the same results of before can be achieved again, even with a more limited actuation effort from the PHEVs.

Simulation 3: To describe the enhanced algorithm, we shall recall first some of the results given in (Griggs et al. (2015)), where premium access strategies to parking facilities were illustrated. In particular, in (Griggs et al. (2015)) it is shown that Equation (8) can be reformulated as

$$prob_i^{EV}(\tau) = \Gamma(\tau)\frac{\overline{D}_i(\tau)}{f_i'(\overline{D}_i(\tau))}, \forall i = 1, ..., n(\tau), \forall \tau = 1, ..., M.. \tag{9}$$

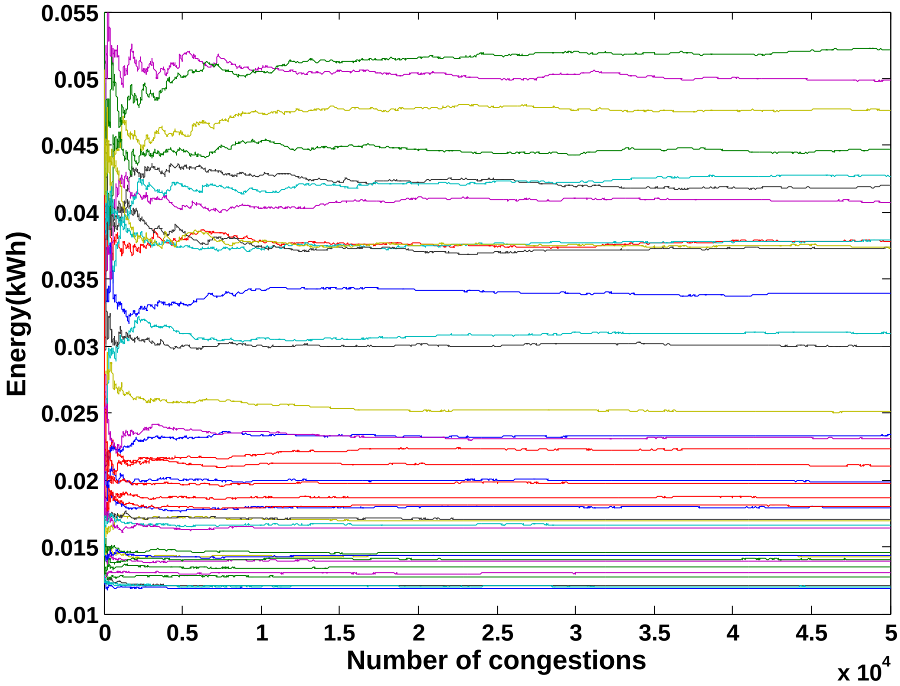

Figure 7. Average of electrical energy consumption of each PHEV at every congestion event.

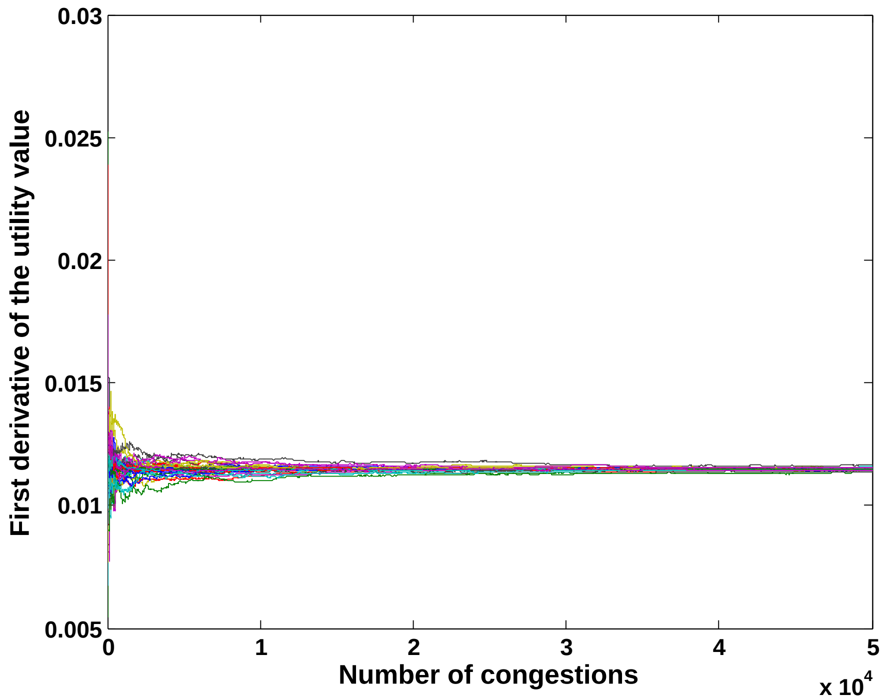

Figure 8. First derivative of the average of energy consumption of each PHEV at every congestion event.

Equation (9) can now be implemented with a small effort from the PHEVs. In particuar, we assume that the infrastructure now broadcasts the value of the scaling factor $\Gamma(\tau)$. Such a value is used to map the ratio into a probability as before, and it can be time-varying in general to give flexibility to the infrastructure to implement some premium access to the forthcoming energy, as explained in (Griggs et al. (2015)). From the perspective of single PHEVs, they can now decide the driving mode by simply recording the average probability to drive in EV mode (at the numerator), and by simply evaluating the derivative of their utility function for that value. As in the AIMD approach described in Subsection 4.2, no inter-agent communication is required. The main difference is that the additive and the multiplicative steps of the AIMD algorithm are simply substituted by the evaluation of Equation (9). Since Equation (9) takes into account the average values of probabilities, a second difference of the new approach is that decisions are not instantaneous but take into account past history. This feature increases the fairness of the proposed solution over stochastic fluctuations of the AIMD approach.

We now evaluate the performance in the usual scenario. In particular, we still adopt the usual SUMO-based simulation set-up. Differently from before, we evaluate the algorithm over a horizon of a few days, to take advantage of the ability of the algorithm to consider the past history of the driving mode. Thus, we repeat the same set-up for a whole month (i.e., 30 days) which leads to a total number of 16200 algorithm iterations. The corresponding simulation results are demonstrated in Figures 9 - 12. Specifically, Figure 9 and 10 demonstrate that the energy regulation objective has been achieved by applying the proposed algorithm. The figures pertain the first day of the simulation, but the same results are obtained in the following days as well. Figure 11 shows that the average of electrical energy consumption of each PHEV indeed converges. Finally, Figure 12 demonstrates that the derivatives of the utility functions correctly converge to a single value as noted in Wirth et al. (2015). Further, according to the KKT conditions as noted in Boyd and Vandenberghe (2004), this implies that the converged results are optimal when the utility functions are strictly convex. Note that figures 9-12 are very similar to figures 5-8. In fact, this shows that a result very similar to that achieved with AIMD can be obtained with a more limited actuation effort from the PHEVs, using the simpler Equation (8).

Comment 7: In principle, the proposed algorithms do not suffer from scalability issues. As an example, we now fix the expected amount of available energy for charging PHEVs to 540 kWh, and we evaluate the performance of the optimal SPONGE algorithm assuming a different number of PHEVs participating to the programme. In particular, we evaluate the algorithm by varying the number of vehicles from 10 to 100. Note that since the overall energy is fixed, this corresponds to assuming an abundant quantity of energy when the number of PHEVs is low, and a scarce amount of energy when the number of PHEVs is large. In each case, we run 100 simulations to calculate the quantities of interest. In this regard, Figure 13 illustrates the average energy allocated to each PHEV per minute of time and Figure 14 demonstrates the average and standard deviation of the total target energy distribution in all cases. Both results reveal that the proposed optimal SPONGE algorithm is able to effectively allocate the available energy to all PHEVs regardless of the number of vehicles participating to the programme.
Note also that a huge number of PHEVs participating to the SPONGE programme could give rise to other issues in terms of practical implementation, e.g., in terms of communication requirements and of computational abilities of the centralised controller to compute the optimal probabilities in real-time for all PHEVs. Although we do not further investigate such situations here, we note that a hierarchical approach could still be adopted by sub-dividing the area of interest in sub-regions, and applying a (conventional) SPONGE scheme to each sub-region with a reduced number of PHEVs at a price of achieving a sub-optimal solution.

5 Conclusions

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 Crisostomi et al. (2014), Wirth et al. (2015)). From a practical point of view, note that the technology to remotely control the driving

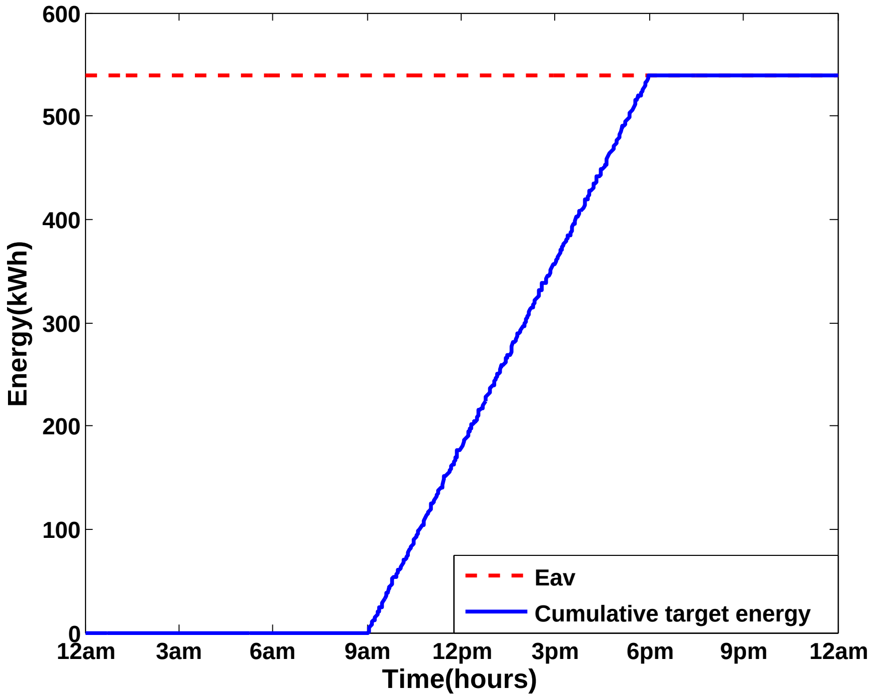

Figure 9. Evolution of the cumulative target energy allocated to the fleet of PHEVs.

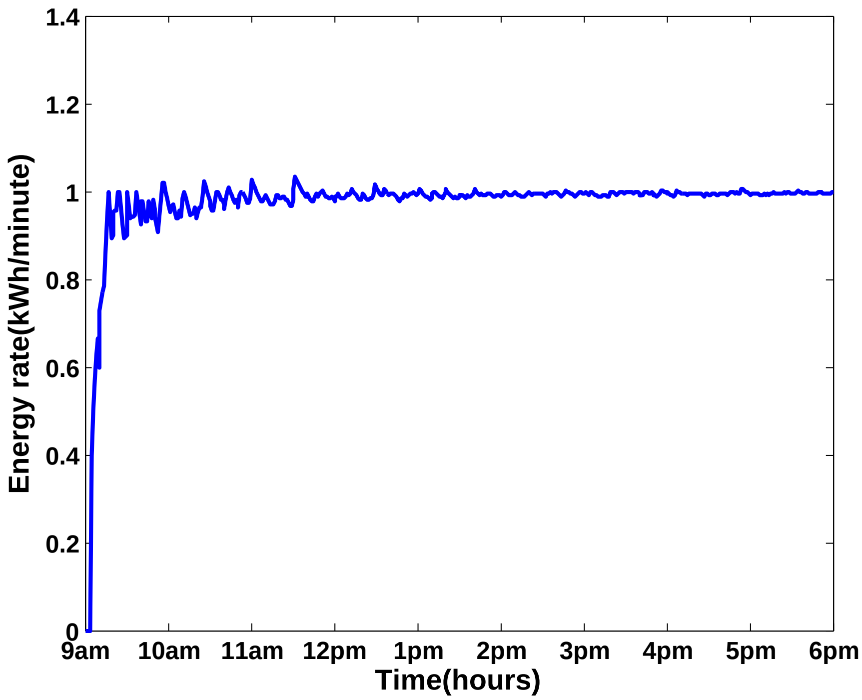

Figure 10. Evolution of the averaged allocation rate of target energy to the fleet of PHEVs.

mode is also already available, as it was developed in (Schlote et al. (2014)) for different purposes.

Our current plan is to extend the preliminary simulation results given in Section 4 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 (Schlote et al. (2014)) to the new case of interest, to remotely control the EV/ICE engine switching. The practical implementation of the

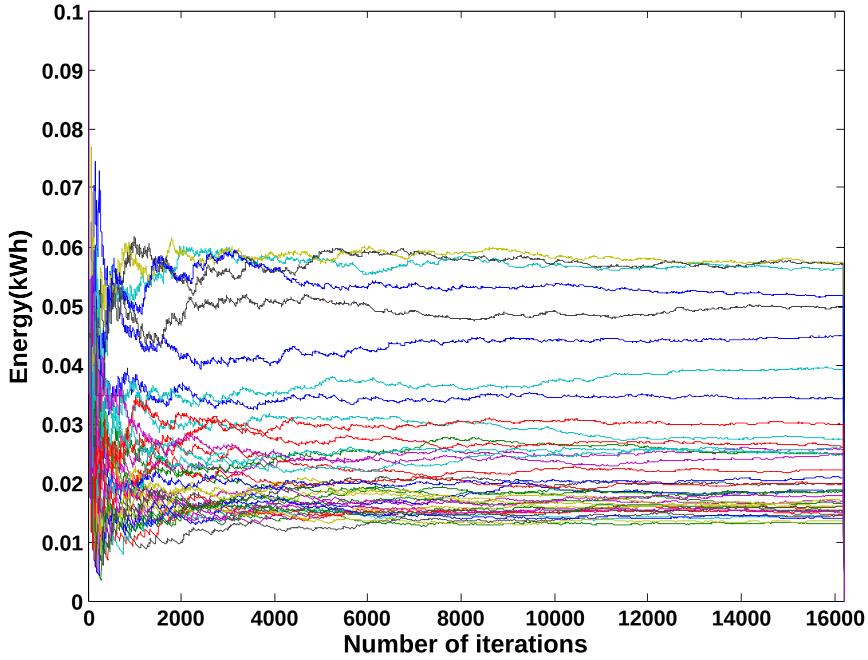

Figure 11. Average of electrical energy consumption of each PHEV.

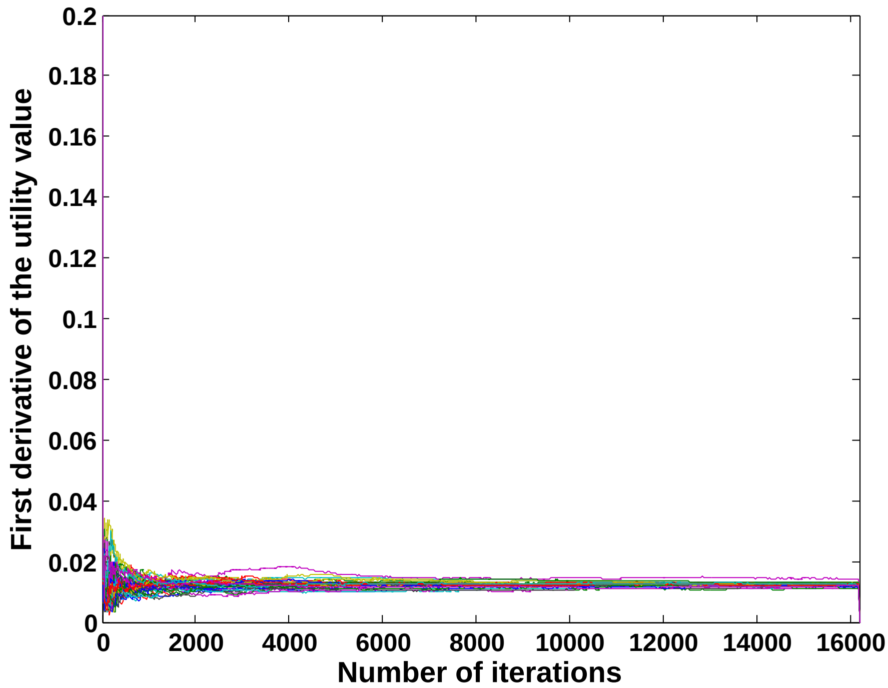

Figure 12. First derivatives of the utility function of each PHEV.

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.

One remaining point concerns the convergence rate of the algorithms. In situations where the AIMD algorithm is used to solve a centralised optimisation in a privacy preserving manner, this is not an issue provided sufficient communication and computational bandwidth exists. In

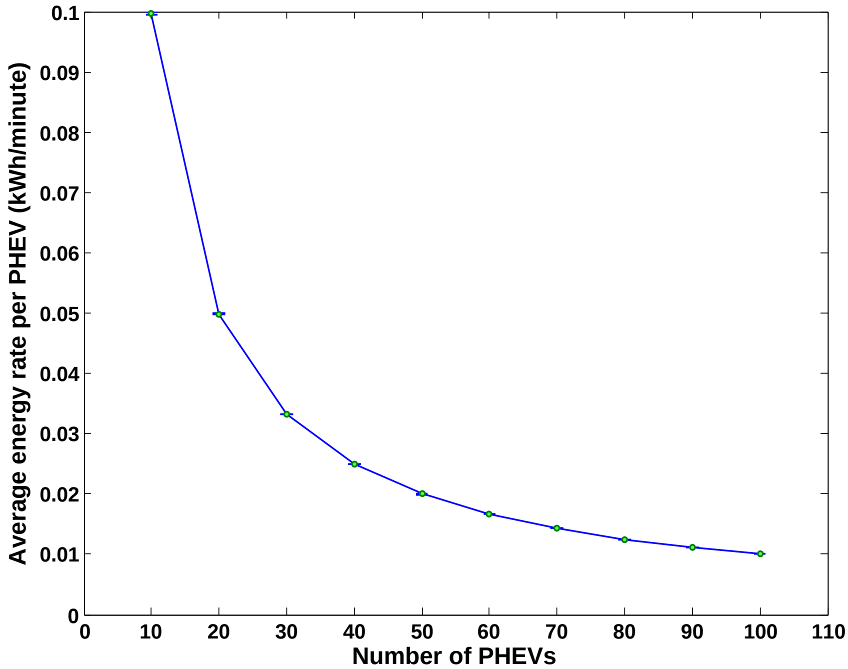

Figure 13. Comparison of the average energy allocated to each PHEV per minute in different cases.

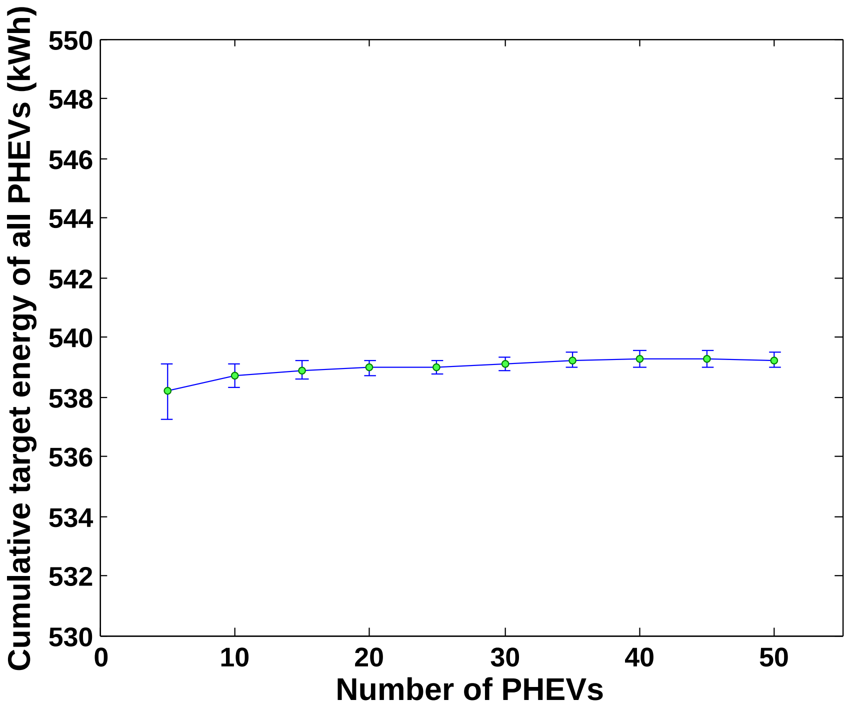

Figure 14. Comparsion of the cumulative target energy allocated to all PHEVs in different cases.

situations where the algorithm is deployed in an on-line manner, then the algorithm makes sense only over longer time-scales. Specifically, we assume that users sign up for a service, and over a long period (say a number of years), compete for available energy.

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