An Intelligent Speed Advisory System for Electric Vehicles

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***Abstract*—Intelligent Transportation Systems (ITS) can be used to involve vehicles and the road infrastructure to cooperatively implement a number of innovative and useful applications. Here, we explore the possibility to adopt a consensus based distributed speed advisory system to determine the optimal recommended speed in urban areas where only electric vehicles are allowed to travel (e.g., in the city centre). The optimality criterion is to maximise the energy efficiency of a fleet of vehicles travelling in the restricted area, and we adopt recently proposed distributed privacy-preserving consensus algorithms to achieve the desired objective.**

I. Introduction

In this paper we are interested in designing speed advisory systems for the case that the fleet of vehicles is composed by only Electric Vehicles (EVs). Such a situation might occur in some sensitive areas in city centres that are closed to conventional traffic, and only allow transit to specific categories of low (or zero) polluting vehicles, see for instance the case of *umweltzonen* in Germany [1]; or a similar problem might occur for a fleet of urban electric buses. The use of electric buses to decrease harmful emissions and noise pollution are becoming widespread in different cities of the world, see for instance the recent cases of São Paulo [2], Louisville in the US [3] or Wien in Europe [4].

Our starting point is the observation that different EVs are designed to operate optimally (e.g., in terms of energy efficiency) at different vehicle speeds and at different loading conditions. In this paper, we address the problem of computing the optimal speed that should be recommended to all vehicles belonging to the fleet of EVs, in order to minimise the overall energy consumption of the fleet; or similarly, to extend their range. Clearly, this task is performed provided that some basic safety and Quality of Service (QoS) requirements are guaranteed (i.e., the optimal recommended speed should be within a reasonable realistic range). As we shall see in the remainder of the paper, the optimal speed heavily depends on how single EVs travel in traffic (e.g., whether air conditioning is on/off and how many people are on-board). Since people might not be interested in sharing such a private piece of information, we are interested in obtaining the optimal solution without requiring single vehicles to communicate personal information to other vehicles or even to a central infrastructure. Accordingly, in our work we adopt a recently proposed algorithm (see [5]) that is a consensus algorithm that somewhat preserves the privacy of individual vehicles, as will be better illustrated later in the paper.

The main contribution of this paper is the development of an ISA system for a fleet of EVs. As far as we know, such an application is novel in the context of ISAs. Accordingly, the proposed approach aims at maximising the energy efficiency of the fleet of EVs, and makes the proposed ISA different with respect to existing conventional ones.

This paper is organised as follows: Section II illustrates a basic model of power consumption in electric vehicles. Such a model will be required to formulate single utility functions that relate the travelling speed with the energy efficiency. Section III recalls the algorithm proposed in [5] and we adapt it to the specific scenario of interest here. Section IV demonstrates some simulation results showing the efficacy and the performance of the proposed approach, and finally Section V concludes the paper and outlines our current lines of research.

II. Power consumption in EVs

Most of the discussion here follows the reference [6], where the ranges of EVs are reported for different brands and under different driving cycles. From what it suggested, power consumption of an EV driving at a steady-state speed (along a flat road) is caused by four main sources:

- *Aerodynamics*: aerodynamic power losses are proportional to the cube of the speed of the EV, and depend on other parameters typical of a single vehicle, such as its frontal area and the drag coefficient (which in turn, depends on the shape of the vehicle);
- *Drivetrain*: drivetrain losses result from the process of converting energy in the battery into torque at the wheels of the car. Their computation is not simple, as

losses might occur at different levels (in the inverter, in the induction motor, gears, etc); in some cases, power losses have been modelled as a third-order polynomial, whose parameters have been obtained by fitting some experimental data (see [6]);

- *Tires*: the power required to overcome the rolling distance depends on the weight of the vehicle (and thus, on the number of passengers as well), and is proportional to the speed of the vehicle;

- *Ancillary systems*: this last category includes all other electrical loads in the vehicle, such as HVAC systems, external lights, audio, battery cooling systems, etc. In this case the power consumption does not depend on the speed of the vehicle and can be represented by a constant term that clearly depends on external factors (e.g., weather conditions) and personal choices (desired indoor temperature, volume of the radio, etc). According to the experimental evaluations from [6], the power losses due to ancillary services uses vary between 0.2 and 2.2 kW.

If we sum up all the previous terms, then the power consumption P_{cons} can be represented as a function of the speed v as:

$$\frac{P_{cons}}{v} = \frac{\alpha_0}{v} + \alpha_1 + \alpha_2 v + \alpha_3 v^2 \tag{1}$$

where on the left hand side we have divided the power by the speed, to obtain an indication of energy consumption per kilometer, expressed in kWh/km. Such a unit of measurement is usually employed in energy-efficiency evaluations. Accordingly, Figure 1 shows a possible relationship between speed and power consumption, obtained using data from Tesla Roadster and assuming a low power consumption for ancillary services of 0.56 kW (i.e., assuming air conditioning switched off). As can be noted from the figure, there is a

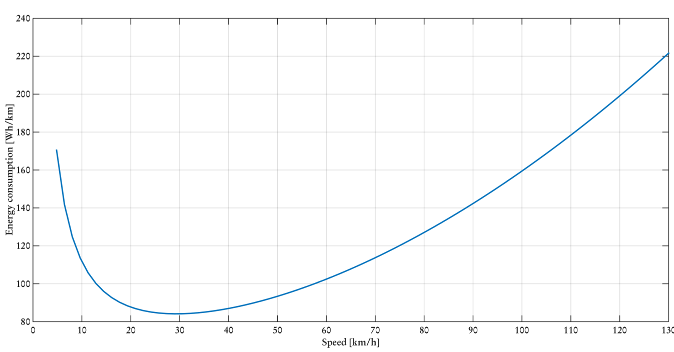

Fig. 1. A typical individual cost function.

large energy consumption when the speed is large (due to the fact that power increases with the cube of the speed for aerodynamic reasons), but also for low speeds, due to the fact that travel times increase, and accordingly constant power required by ancillary services require more energy than the same services delivered with high speeds.

In order to implement the proposed ISA system, we shall further assume here that vehicles are equipped with a V2X (Vehicle-to-Infrastructure (V2I) and Vehicle-to-Vehicle (V2V)) communication system, and can exchange information with other vehicles within a reasonable range, and with the infrastructure. For instance, each EV could be equipped with a specific communication device (e.g., a mobile phone with access to WiFi/3G networks). Note that such a technological equipment, though usually already available in most EVs, will further have an impact on the energy consumption pattern.

III. Algorithm

We assume that N electric vehicles have access to a common clock. Let $k \in \{1, 2, 3, ...\}$ be a discrete time instant in which new information from vehicles is collected and new speed recommendations are made. The scalar variable $s_i(k)$ denotes the recommended speed of the vehicle $i \in \underline{\mathrm{N}} := \{1, 2, ..., N\}$ at time k. Further, let $\mathbf{s}(k)^{\mathrm{T}} := [s_1(k), s_2(k), ..., s_N(k)]$ be the vector of recommended speeds for all vehicles at time k. Denote by N_k^i the set of neighbours of vehicle i. The feedback loop is shown in Figure 2.

In addition, we assume that each vehicle i can evaluate a

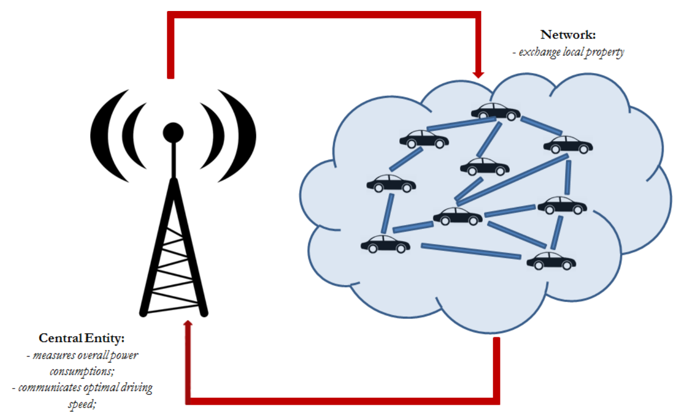

Fig. 2. Feedback loop for the Intelligent Speed Advisory system.

function f_i that determines its average power consumption at a given steady-state speed, according to equation (1). Note that in order to achieve this, it is necessary that the vehicle both knows its parameters in the function, and also monitors the functioning of some electric appliances on-board (e.g., the intensity of the HVAC system or whether the radio is switched on). We shall assume that functions f_i are convex, continuously differentiable and with a Lipschitz continuous first derivative f_i' which is assumed with positive bounded growth rate in the domain of interest $\mathcal{D}$. We assume that the recommended speed can vary within the domain $\mathcal{D} = [5, \ldots, 130]$, which is a realistic range of speeds, expressed in km/h. Then the requirement on the derivative can be expressed as

$$0 < d_{\min}^{(i)} \leq \frac{f_i'(a) - f_i'(b)}{a - b} \leq d_{\max}^{(i)}, \tag{2}$$

for all $a, b \in \mathcal{D}$ (i.e., for reasonable steady-state speeds) such that $a \neq b$, and suitable positive constants $d_{\min}^{(i)}$, $d_{\max}^{(i)}$. Notice that Equation (1) fulfills all the previous requirements, and thus, the previous assumptions are usually satisfied in the application of interest here. In this context, we consider the following problem:

Problem 1: *Design an ISA system for a fleet of electric vehicles connected via V2X communication systems. The speed recommended by the ISA is the speed that minimises the total power consumption of the fleet of vehicles.*

We now formulate the problem as follows:

$$\begin{aligned} \min_{\mathbf{s}\in\mathbb{R}^N} \quad & \sum_{j\in\underline{\mathbf{N}}} f_j\left(s_j\right), \\ \text{s.t. } & s_i = s_j, \ \forall i \neq j \in \underline{\mathbf{N}}. \end{aligned} \tag{3}$$

This problem is an optimised consensus problem and can be solved in a variety of ways (for example using ADMM [7]–[9]). Our focus in this present work is not to construct a fully distributed solution to this problem, but rather to construct a partially distributed solution which allows rapid convergence to the optimum, without requiring the vehicles to exchange information that reveal individual cost functions to other vehicles. This is the privacy preserving component of our problem statement.

Comment: We shall not address Problem 1 with the objective to calculate the optimal speed to be recommended to all the vehicles in one step. On the other hand, we propose an iterative algorithm that at each step yields individual recommended speeds that will eventually converge to the same value under a consensus constraint. In doing this, we shall assume that the vehicles will be compliant with the recommended speed (this might be more realistic for public transportation rather than for single vehicles, but non-compliance with the recommended speed is not investigated here and left for future work).

To solve (3) we use an iterative feedback scheme of the form

$$\mathbf{s}\left(k+1\right) = P\left(k\right)\mathbf{s}\left(k\right) + G\left(\mathbf{s}\left(k\right)\right)e, \tag{4}$$

where $\{P\left(k\right)\} \in \mathbb{R}^{N\times N}$ is a sequence of row-stochastic matrices[1], $e \in \mathbb{R}^N$ is a column vector with all entries equal to 1, and $G : \mathbb{R}^N \mapsto \mathbb{R}$ is a continuous function with some assumptions to satisfy as we shall see in Equation (9). Similar algorithms were proposed and studied, among others, in [10], [11]; they were further investigated in [5], where guarantees for convergence were also given.

Here, we shall assume that (3) has a unique solution. Then, according to elementary optimisation theory, if all the f_i's are strictly convex functions, then the optimisation problem (3) has a solution if and only if there exists a $y^* \in \mathbb{R}$ satisfying

$$\sum_{j=1}^{N} f_j'(y^*) = 0. \tag{5}$$

In this case by strict convexity y^* is unique and the unique optimal point of (3) is given by

$$\mathbf{s}^* := y^* e \in \mathbb{R}^N. \tag{6}$$

In order to obtain convergence of (4) we select a feedback signal

$$G\left(\mathbf{s}\left(k\right)\right) = -\mu \sum_{j=1}^{N} f_j'\left(s_j\left(k\right)\right). \tag{7}$$

and we obtain the dynamical system

$$\mathbf{s}(k+1) = P(k)\mathbf{s}(k) - \mu \sum_{j=1}^{N} f_j'(s_j(k))e, \qquad \mu \in \mathbb{R}. \tag{8}$$

In [12] it is shown that if $\{P(k)\}_{k\in\mathbb{N}}$ is a uniformly strongly ergodic sequence[2] and μ is chosen according to

$$0 < \mu < 2\left(\sum_{j=1}^{N} d_{\text{max}}^{(j)}\right)^{-1}, \tag{9}$$

then (8) is uniformly globally asymptotically stable at the unique optimal point $\mathbf{s}^* = y^* e$ of (3). More details, and the mathematical proofs can be found again in [5].

Thus, we proceed as follows: For each k we define the $P\left(k\right)$ as

$$P_{i,j}\left(k\right) = \begin{cases} 1 - \sum_{j\in N_k^i} \eta_j, & \text{if } j = i, \\ \eta_j, & \text{if } j \in N_k^i, \\ 0, & \text{otherwise.} \end{cases}, \tag{10}$$

where i, j are the indices of the entries of the matrix $P\left(k\right)$, and $\eta_j \in \mathbb{R}$ is a weighting factor. For example, a convenient choice η_j is $\frac{1}{\left|N_k^i\right|+1} \in \left(0, \frac{1}{N-1}\right)$, where $|\bullet|$ denotes cardinality, giving rise to an equal weight factor for all elements in the reference speed vector $\mathbf{s}\left(k\right)$.

Comment: As an example to illustrate the matrix $P(k)$, let us consider a simple network with three EVs at a given time step k. We assume the followings: the first EV is able to receive the info only from the second EV; the second EV is not able to receive any info from its neighbours; the third EV is able to receive info from all EVs; then the corresponding matrix $P(k)$ can be shaped as:

$$P(k) = \begin{bmatrix} \frac{1}{2} & \frac{1}{2} & 0 \\ 0 & 1 & 0 \\ \frac{1}{3} & \frac{1}{3} & \frac{1}{3} \end{bmatrix}$$

The assumption of uniform strong ergodicity holds if the neighborhood graph associated to the problem has suitable connectivity properties. If sufficiently many cars travel in the city centre area, it is reasonable to expect that this graph is strongly connected at most time instances. Weaker assumptions are possible but we do not discuss them here for reasons of space; see [13] for possible assumptions in this context. In any case, note that the time-varying communication graph makes the system (4) become a switching system.

[1] Square matrices with non-negative real entries, and rows summing to 1.

[2] That is, for every $k_0 \in \mathbb{N}$ the sequence $P(k_0)$, $P(k_0+1)P(k_0)$, …, $P(k_0+\ell)\cdots P(k_0)$, … converges to a rank one matrix. See [12] for further details.

Now, we propose the following Optimal Decentralised Consensus Algorithm for solving (3). The underlying assumption here is that at all time instants all EVs communicate their value $f'_j(s_j(k))$ to the base station, which reports the aggregate sum back to all EVs. This is precisely the privacy preserving aspect of the algorithm, as EVs do not have to reveal their cost functions neither to the base station, nor to other vehicles. Some implicit information (i.e., the derivative of the cost function at certain speeds) is indeed revealed to the base station but not to other EVs in the fleet.

Algorithm 1 Optimal Decentralised Consensus Algorithm

for $k = 1, 2, 3, ..$ **do**
  for each $i \in \underline{\mathbf{N}}$ **do**
    Get $\tilde{F}(k) = \sum_{j \in \underline{\mathbf{N}}} f'_j(s_j(k))$ from the base station.
    Get $s_j(k)$ from all neighbours $j \in N_k^i$.
    Do $q_i(k) = \eta_i \cdot \sum_{j \in N_k^i} (s_j(k) - s_i(k))$.
    Do $s_i(k+1) = s_i(k) + q_i(k) - \mu \cdot \tilde{F}(k)$.
  end for
end for

IV. Simulation

We now give some preliminary results, obtained in Matlab simulations.

A. Consensus Algorithm

The first simulation aims at showing that the algorithm illustrated in Section III naturally behaves as a consensus algorithm. For this purpose, we consider a city centre with 100 EVs running for a whole hour. In the first 16 minutes, the vehicles are assumed to be travelling at different speeds that have been chosen in a random fashion. Then, we let the ISA system start working after 10 minutes, and the vehicles start travelling at the recommended speed in a few minutes, as shown in Figure 3. The corresponding energy consumption is shown in Figure 4.

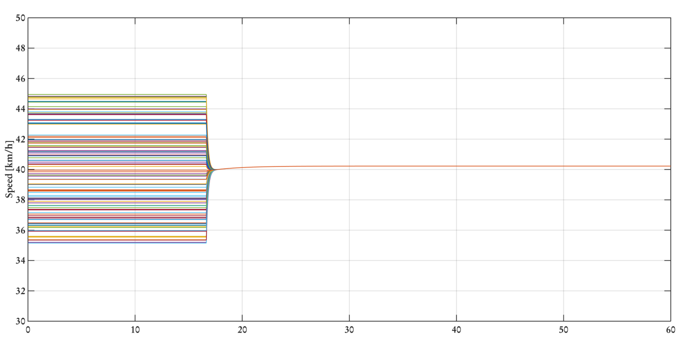

Fig. 3. The speeds of the EVs converge to the optimal speed recommended by the ISA system.

B. Speed Optimality

The second simulation aims at showing that the recommended speed is in fact more energy convenient that other

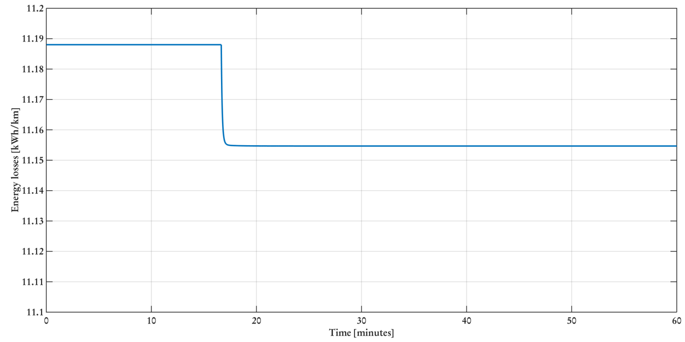

Fig. 4. Energy consumption changes when the vehicles start travelling at the recommended speed.

speeds. For this purpose, we assume that a fleet of 100 vehicles travels in the city centre for an hour. In the first 20 minutes of the simulation, the vehicles travel at the optimal speed, in the second 20 minutes, they travel at another recommended speed of 30 km/h, and finally in the last 20 minutes they travel at a speed of 50 km/h. We assume that the change of speed in the two last stages occur instantaneously, since there is no requirement to iteratively compute an optimal speed. In the first part, we assume that the communication graph among the EVs changes in a random way (i.e., at each time step an EV receive information from a (possibly empty) subset of vehicles belonging to the fleet). This is a simplifying assumption that can be justified by assuming that in principle all vehicles might communicate to all the other vehicles (i.e., they are relatively close), but some communications might fail due to obstacles, shadowing effects, external noise, or other. We tuned our parameters in Algorithm 1 as $\eta = \mu = 0.001$. Finally, we simulated different utility functions for the different EVs by assuming a random number of people inside each car (between 1 and 5 people) with an average weight of 80 kg and by assuming a different consumption from ancillary services within the typical range of $[0.2, 2.2]$ kW. The utility functions are shown in Figure 5. The evolution of the speeds of the EVs are shown in Figure 6, while the average energy consumption is shown in Figure 7.

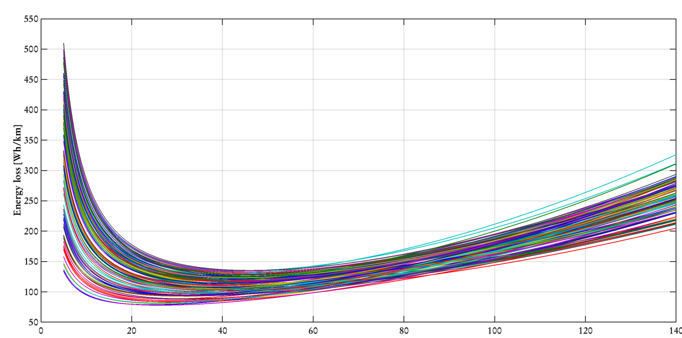

Fig. 5. Utility functions chosen for the set of 100 vehicles. Note that all functions are convex, and have a personal optimal speed usually between 30 and 40 km/h, which is a reasonable speed for driving in the city centre.

V. Conclusion

In this paper we presented a novel application for Intelligent Speed Advisory systems, related to determining

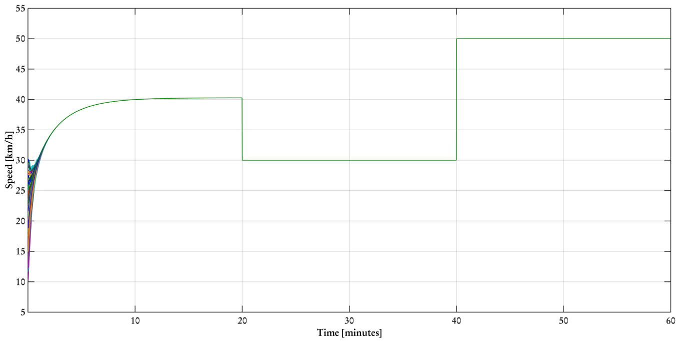

Fig. 6. Three recommended speeds are suggested in the second simulation, and in the first 20 minutes the EVs travel at the optimal one.

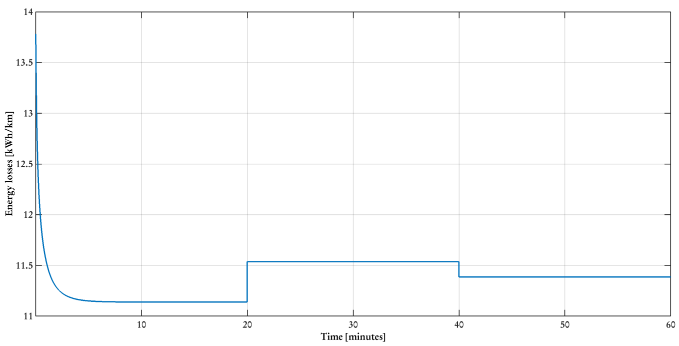

Fig. 7. Energy consumption is minimum when the vehicles travel at the optimal recommended speed.

the optimal speed that should be followed by a fleet of EVs, with the specific objective to improve their energy efficiency or, in other words, to collaboratively extend their travelling range. The proposed idea has been implemented by adopting a distributed consensus algorithm that has the feature to preserve privacy of the personal information, which we believe is an important point to motivate people to effectively collaborate.

Preliminary results have presented through Matlab simulations. Current work is focussing on redoing the simulations in a more realistic mobility simulator (e.g., SUMO), in order to further investigate a couple of aspects that have been neglected in the presented work: (i) recommended speeds can be communicated, for instance, by establishing a speed limit in the area of interest. However, the speed indicated in the speed limit, and the true steady-state of vehicles are clearly different. Realistic transportation simulations will allow us to identify the most convenient speed limit that in turn would result in an average speed close to the optimal one. Clearly, such an analysis is affected by the specific characteristics of the city centre of interest. Also, (ii) we have currently neglected the true communication network underlying the fleet of EVs, and have simply assumed that communications could occur in a random fashion. In the future, we shall further include a realistic communication network in the mobility simulator to validate the effectiveness of the proposed consensus algorithm for the specific application of interest here (e.g., in terms of convergence speed).

Acknowledgment

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