Improving Electric Vehicle Autonomy in the Smart City Concept

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ABSTRACT

Organizing automobiles in a city is challenging due to the sensitive data that need to be disclosed. Information that can be utilized to identify a car and provide some useful characteristics about it is among the large amount of data that can be collected from an automobile. This operation will be easier if the vehicles are placed on a specific platform based on the smart city concept. Even if sensors and cameras are installed around the roads and the city, having the vehicle information will be more useful. The current study tries to demonstrate how it is feasible to improve vehicle autonomy by initially enhancing the vehicle's energetic performance, based on the smart city idea. Intelligent control topology serves as the foundation for the exposed energy management protocol. The suggested concept is created and the associated results are displayed using the Matlab Simulink platform.

Keywords-electric vehicle; power management; communication; optimization; neural networks; drive cycle mode; smart city

I. INTRODUCTION

Electric Vehicles (EVs) are rising to prominence as a vital mode of mobility. Electrical transportation equipment includes a wide range of types and categories, such as the double-wheel electric scooter, the four-wheel electric vehicle for personal transportation, and electric buses and rails [1, 2]. A specification that characterizes all these electrified transportation tools is the energy storage element, which basically is an electric storage battery. The latter is the most important factor in the establishment of vehicle autonomy and of the possible distance that can be made when using any EV [3, 4]. On the other hand, this type of battery entails certain risks during transportation, such as the risk of fire or that of an explosion in case high temperatures are reached. All these weaknesses deteriorate the EV usage as a transportation tool. Therefore, researchers strive to avoid the aforementioned problems by providing more solutions to them and employing technologies to make any EV's use secure and improve its battery autonomy. In fact, these two objectives were treated in more than one manner and methods. Considering the vehicle autonomy issue, some works presented several solutions for enhancing the former. Some strategies concentrated on minimizing the aerodynamic effect on the vehicle body to decrease the air reaction at high speeds. Some researchers tried to minimize vehicle weight, so that it could be possible to save a greater amount of power for the traction phase [5]. Engineers have been also looking for ways to construct traction motors with increased power, which consume less energy with higher rentability. For this purpose, specialized AC machines were proved to be effective transportation tools [6, 7]. Different forms of power management have appeared in the literature. Some researchers contributed to the electrical traction way. Also, certain modified vector control strategies, or direct torque control topologies, engaged to get a better response from the traction machine and to decrease power loss in the transition phases, have been presented [8, 9]. Other solutions to manage the recharge and discharge phases in the Hybrid Electric Vehicle (HEV) models were provided in [10]. Those techniques, based on intelligent control, have demonstrated satisfactory energy consumption and greater autonomy [11-13]. Numerous industries have been highly benefited from smart cities in that they have managed to ease traffic congestion and shorten public transit wait times in the transportation sector. Centralized video networks improve security by making it easier to identify and monitor suspects. With more accurate estimates of monthly energy requirements and more effective power management, the energy sector is benefited as well. Multiple studies have highlighted that the accident ratio has been decreased as a result of the use of smart city technologies. Specifically, a research carried out in Barcelona, Spain, discovered that the implementation of smart city infrastructure, such as cameras and sensors, resulted in a 20% decrease in traffic accidents. In addition, a study in Singapore revealed that the employment of autonomous vehicles and smart traffic management systems led to a 20% decrease in traffic accidents. Furthermore, a study in Los Angeles disclosed that the implementation of a smart traffic management system led to a 16% reduction in traffic accidents. These statistics demonstrate the potential for smart city infrastructure to significantly eliminate the accident ratio and improve safety [14, 15].

An intelligent communication protocol between vehicles was presented in [16, 17], aiming to produce a database for several vehicles, which includes each vehicle's energy experience. Following that, a learning phase will be generated to create an adaptive model that can provide each trajectory with a better drive approach [18, 19]. All the related parameters and variables were defined and associated to formulate a mathematical problem.

II. THE CONCEPT OF CONNECTED ELECTRIC VEHICLE

Two versions of EVs have been developed: HEVs and Total Electric Vehicles (TEVs). An electrical motor that can function as either the primary active motor or a backup active motor should be positioned. The HEV version allows for this [9]. There are two types of cars: one with an electrical power system and the other without. The hybrid variant is the only one with an ICE and a fuel tank. A HEV can be classified as series or as parallel depending on where the hybrid electrical motor is situated [10].

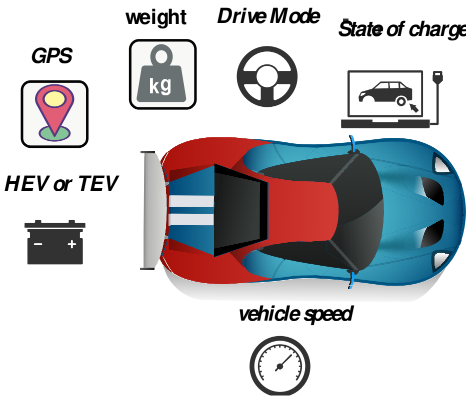

Fig. 1. Concept of the connected vehicle with information to be exchanged.

The concept of a vehicle can be modeled in two different ways when the vehicle is on the road, namely with and without speeds [20]. The EV typically travels a distance s during each stop-and-go phase by accelerating, maintaining a constant speed of v, and decelerating. The related energy formula during the constant velocity period can be expressed as:

$$E_2 = \int_0^t (Au^2 + (B + Cu))udt \tag{1}$$

where A, B, and C are defined as follows:

$$\begin{aligned} A &= \frac{1}{2}\rho A_f C_D \\ B &= C_r mg \\ C &= C_u mg \end{aligned} \tag{2}$$

In the acceleration form, the revolted energy consumption model can be expressed as in (2), where a is the acceleration ratio and u is the speed of the car.

$$\begin{aligned} E_1 &= \int_0^{u/a} (ma + A(at)^2 + (B + Cat))atdt \\ &= \frac{1}{2}mu^2 + \frac{Au^4}{4a} + \frac{Bu^2}{2a} + \frac{Cu^3}{3a} \end{aligned} \tag{3}$$

So, the global energy consumption model regroups the two previous energy equations. The corresponding model for multiple stops and for a giving drive cycle can be expressed as in (4), where n is the vehicle stop number, m is the vehicle mass, g is a constant force factor, C_r and C_u are the resistive torque and the acceleration torque, respectively [11]:

$$E(u,n) = (n+1)(E_1 + E_3) + E_2(u,n) \tag{4}$$

III. THE CONNECTED VEHICLES IN THE SMART CITY CONCEPT

A. Smart City Concept (Database) and Connected Vehicles

The concept of smart city and connected vehicles has several fields to be discovered and ameliorated. The relationship between these two concepts can be discussed for improving road safety or enhancing vehicle and driver security.

It can be also used for delivery service and time optimization or similar to road trajectory optimization and energy inside vehicle management.

This study aims to demonstrate that the integration of EVs within smart cities can enhance vehicle autonomy. In reality, every car has a different energy consumption pattern depending on internal and external circumstances. A vast information database that gathers more than vehicle energy management experience can be found in vehicles that drive on the same road. An optimization system will then generate the best energy experience, which will be shared with other cars on the road in order to reduce the energy cost.

1) Principle of Information sharing between Vehicle and Database

The principle of exchanging information between a vehicle passing through a database center, which regroups the energetic identity of the vehicle through sensors installed around and on vehicles, is described in Figure 2. More than one vehicle will cross the same trajectory on the map. Those vehicles were classified by the time of entrance to the trajectory, and the oldest one was the first vehicle that entered the trajectory. The last vehicle which enters the road will be the newest car, and it is the vehicle that needs to know the best way to manage power on this road.

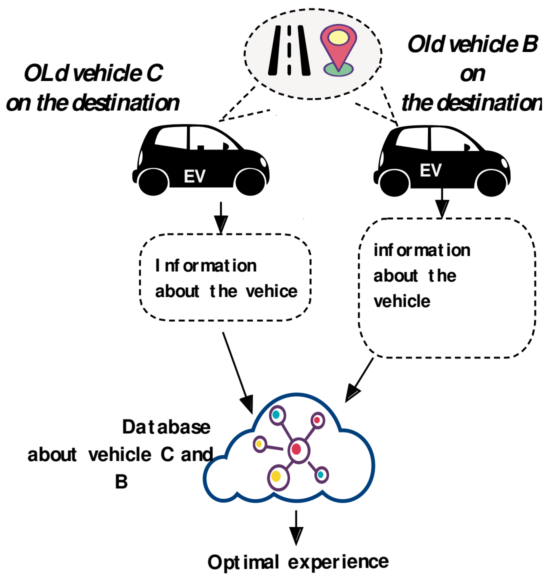

Fig. 2. Principle of information sharing between vehicles on the same trajectory.

2) Vehicle and Smart City Relationship

In this concept, the vehicle is supposed to be inside the city limits, where the smart city concept has all the required apparatus for communication protocols and basic sensors and equipment. Mixing the Internet of Things (IoT) and vehicle-to-vehicle becomes a solution for managing the power of the vehicle and increasing the security factor inside the city. Much information about the vehicle and its surroundings will be available. Knowing the vehicle's GPS position will help determine its slope and any potential needs. It will be easier to see the conductor mode of the car by using the face detection system. Knowing the status of the batteries and the fuel will also help decide whether or not to start the hybrid mode.

Knowing the relevant torque on the machine is just as crucial as the vehicle weight. Each piece of information will, therefore, be essential for reducing power use. Knowing the road situation and the road traffic will also be valuable for obtaining information regarding future decisions. Those data will be regrouped and classified from each connected vehicle for building an Identification Energetic Label (IEL) for each vehicle. Creating a flawless archive is difficult since similar car models with the same fitted sensors and the same architecture are not readily available in the same zone. In this initial study, it will be assumed that all linked automobiles have exactly the same attributes in order to simplify the application. More than just a car connected to the cloud database is needed in order to start developing a database. Each car will display its information, as seen in Figure 3.

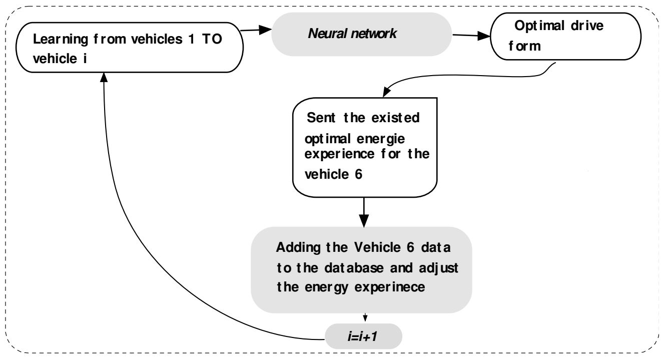

Fig. 3. Description of the algorithm function.

3) Communication Protocols

The system will initially inquire about the car model, the vehicle position, and the target trajectory if the original vehicle is brand-new for this Database. The vehicle will be placed in the appropriate category. The employed algorithm will compare the vehicle information with other existing information inside the Database. If there is a similarity between two scenarios for the vehicle state in the Database, the algorithm will select the best scenario from those that are already possible. In the absence of new information, the system will update the Database to reflect this vehicle category and begin a new learning phase. After that, a brand-new energy-optimal condition will exist. Until a different optimal condition is provided by the system, this vehicle will retain its energy experience. For the hybrid vehicle category, the automobile will be questioned about its energy usage, including the way it consumes fuel and electricity and the quantity of energy it stores. The speed of the car will also be questioned. All that data must be reachable from a specific km distance. If the vehicle is not categorized as a pure electric vehicle, the system will essentially inquire about the amount of electricity consumed, the speed, and the acceleration of the vehicle over the last specific km distance. The car requests to join the

Database if one of those critical variables of information is missing.

B. The Learning Algorithm Discerption

Since the Database contains information from several sources, including multiple connected vehicles, the system will aggregate most of the vehicle-identified data into numerous vector inputs. Equation (5) presents an information vector that contains the desired data for the pure electric vehicle number i. The vector involves information on the vehicle's weight, speed, and State Of Charge (SOC). Equation (6) exposes the desired output signal that contains the necessary information to be used by the algorithm. All these vectors will be utilized in order to reduce the global equation system exposed in (7).

$$X_{TEV}(i) = [W(i) \quad V(i) \quad SOC(i) \quad D_{A\to B}] \tag{5}$$

$$Y_{TEV}(i) = [ACC^{*}(i) \quad V_{low}(i) \quad V_{max}(i)] \tag{6}$$

The selected neural network algorithm is based on the given architecture in Table I.

TABLE I. NEURAL NETWORK ARCHITECTURE FOR THE TRAINING PHASE

Input layer	Hidden layers	Output layer	Learning function
5	2	1	Sigmoid

C. The Objective Function

Finding the optimal driving cycle that reduces the EV's whole trip energy consumption is the ideal issue that can be expressed as follows:

$$\min E(v,n) = f(a) \tag{7}$$

Therefore, the energy consumption factor can be decreased by adjusting the acceleration ratio. It is crucial to note that, for the chosen trajectory, the vehicle speed cannot be higher than the vehicle limit speed set by the other cars.

IV. PROTOTYPE DESCRIPTION AND RESULTS

Six linked cars will be employed in an attempt to describe the working algorithm. Five cars will build the Database and the sixth will act as a visitor who will request an optimal energy experience. Assumedly, the trajectory for each automobile is the same. The learning system will make use of the data from the five known vehicles, as displayed in Figure 3. The program will first examine those cars in an effort to generate the best possible energy experience. The learning system will look for the best energy experience and determine the best driving technique for a new automobile when one is present and requests it in order to drive it in the desired trajectory. Following that, the algorithm will resume and attempt to enhance its database by adding the automobile data. The learning algorithm will make use of the saved data to provide the best possible energy experience and then the corresponding best drive method.

Figure 3 depicts four pieces of car information in relation to the acceleration form and its corresponding speed behavior. It is clear that some differences in the drive mode exist at 100, 200, 500 s for the three cars. Also, at 1500 s, it can be observed that each car has a different drive method. The car's weight is 1200 kg and their trajectories are fixed at 2500 s, while their weight is assumed to be the same.

With this data, the neural network algorithm will attempt to understand how this vehicle type behaves for a specific acceleration. The learning phase was developed over 1500 iterations, which corresponds to the smallest learning error and an execution duration that is feasible. As the database information is large enough, in relation to the vehicle drive evolution in time function, the rest of the result analysis will be kept on a zoom section, for instance, 200 s to 340 s. As it is required to follow the energy consumption factor, Figure 5 shows the related energy consumption form for the given drive section illustrated in Figure 4. It can be noticed that some differences exist in the energy curves for three vehicle cases.

The energetic experience in the database is presented in Figure 5. The zoomed zones disclose the EV feedback in relation to the modified driven cycle form that was utilized to operate the car. Approximately, all four energy experiences are the same, with just minor variations. For instance, it appears that the driver of the first electrical car operated the vehicle differently from the other examples, particularly in the 200–300 s range. Every car in the other vehicles was driven using a unique driving technique. For the learning phase, each of these experiences and their SOC forms were employed.

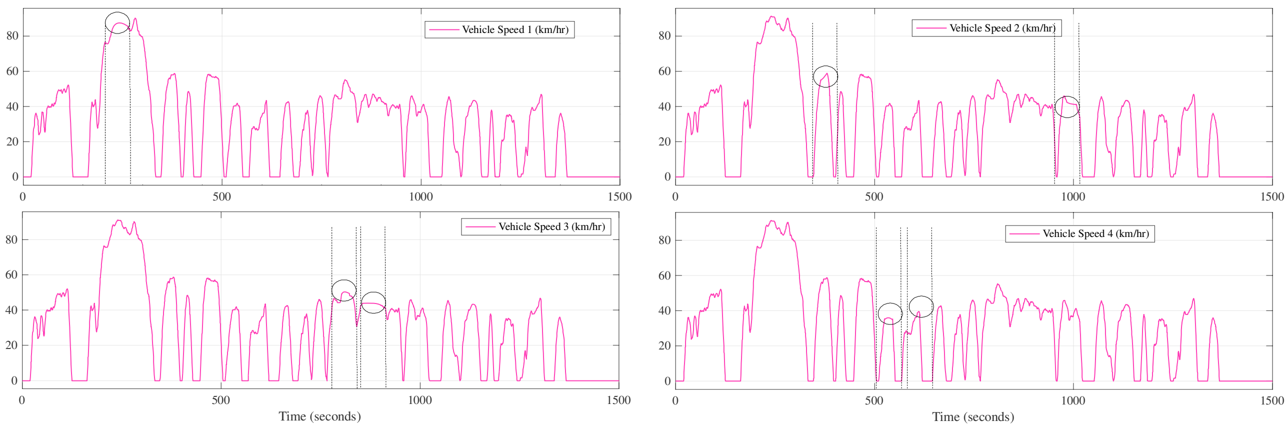

Fig. 4. Acceleration forms for four cars in the Database for the same trajectory with similar speed limits and some modifications on the drive method.

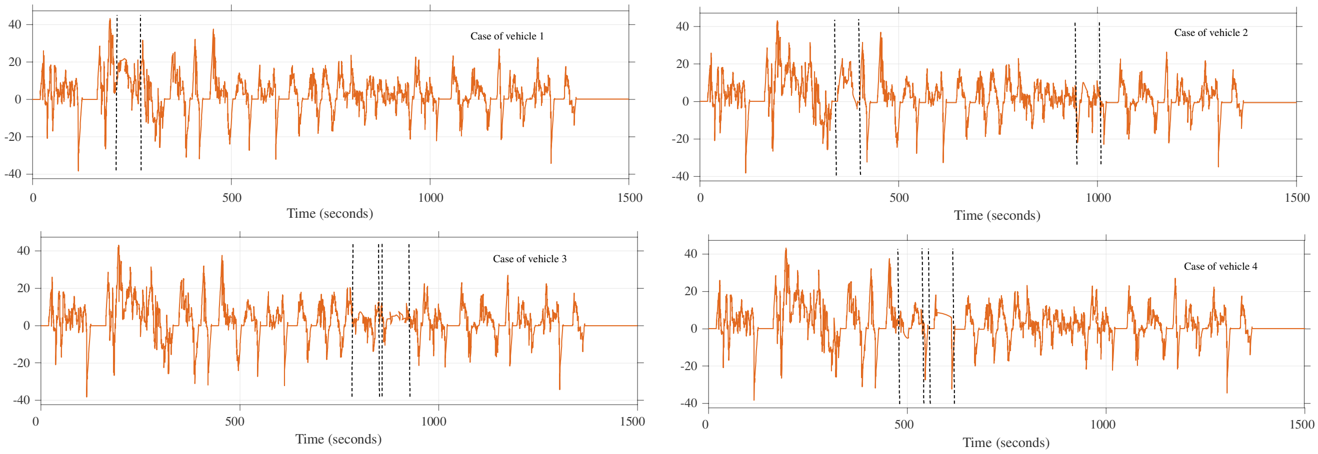

Fig. 5. Energetic experience of the four vehicles.

After running the corresponding neural block, the overall algorithm will have finished. It is easy now for any vehicle that asks for an optimal energy experience to have what is needed. The results related to the guest vehicle can be seen in Figure 6. The adaptability and the efficiency of the obtained neural network bloc will be tested on a new drive cycle form, as is in Figure 6. This Figure demonstrates the optimal trajectory drive cycle obtained by the neural network as well as two different cars using the same trajectory with a different acceleration form. The related electrical motor speed form can also be spotted, while few modifications are observed. When a vehicle employs its own drive cycle form or the best drive cycle model, Figure 6 displays the associated SOC form for each scenario. In conclusion, it is evident that there is a difference in the SOC and if the best course is taken, the SOC will end up being greater than in the other scenarios.

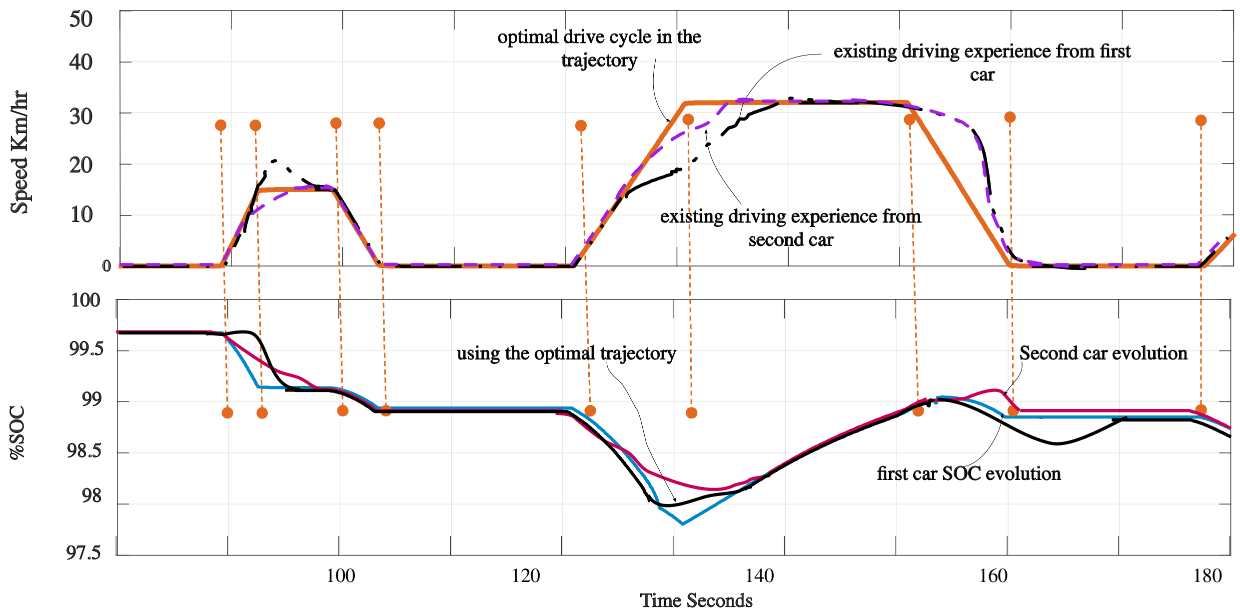

Fig. 6. Optimal drive cycle from two existing drive cycle forms.

Figure 6 exposes the related battery SOC for three different cars. One of them has used the optimal drive cycle given by the neural network and the others have implemented their own drive method. It can be seen that the SOC is different between the three cases, especially in the up-slop, at 10 s, 50 s, 90 s and from 150 to 180. This is due to the intervention of the optimization block, which has concluded that in these instances, the acceleration slope is not necessary to be maximum and can be decreased. The optimization algorithm successfully applied to various slopes, maintained the battery's SOC at its initial value by the end of the simulation period. This consistency is partly due to the car model's energy regeneration feature on down-slope roads, which explains the increases in battery SOC during certain periods.

V. CONCLUSION

In this paper, a new energy management topology is proposed, which can improve vehicle autonomy and enhance the use of electric vehicles. The proposed concept has been based on the smart city concept, where more information acquisition tools exist and information exchange is easy. The idea is to create a database for every car, containing data from various sensors, both inside and outside the vehicle. This database will be organized and utilized during the training process to train a neural network that can determine the best drive cycle strategy for each unique set of road conditions. A multiple drive cycle form was employed to construct the concept, which was then evaluated in a specific drive cycle example.

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