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Original scientific paper

Enhancing the Electrified Transportation System with the IOT Tools Placed Around a City

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Abstract: Electric vehicles and smart city concepts based on IoT tools seem to be high-technology solutions that impact the transportation system, road safety, and road management sectors. In a big city where the number of vehicles is high, and the city roads are close and overlapped, road safety and vehicle management seem difficult. This is why one of the major solutions needs to use high-technology sensors based on IoT equipment and technology. In this context, this paper is exposed in order to use the benefit of the smart city, based on the IoT technology for enhancing the electric vehicle energy consumption mode, and this is by controlling the vehicle trajectory from two points in a road. The principle of the proposed work is based on the neural network concept, which uses a large database of information for making learning in order to find the optimum trajectory from various similar cars that have used the same trajectory for moving from position A to position B. The simulation was made on Matlab Simulink platform and the results were then exposed and discussed.

Keywords: buildings; neural network; optimization; power management; storage system efficiency; transportation sector, vehicle to sensors

1 INTRODUCTION

Electric vehicles become one of the most important transportation tools . Many models and categories exist in the world, such as the double and four-wheel electric Scotter/vehicle for personal transportation or electric busses and tracks, all of which are classified as electrical transportation tools. Basically, the majority of these transportation tools is related to the capacity and ability of the storage system used inside, as maximum capacity and energy management method [1-6]. This essential bloc has a direct impact on vehicle autonomy and on the possible running range that will characterize the electrical transportation tool [7, 8]. On the other side, this element presents the danger element in this transportation loop. Any risk of fire or high temperature can cause an explosion. In relation to the majority of cited works and research, the battery storage system has the biggest impact on the viability and safety of this transportation tool. If this element is not safe enough or not efficient enough, it is possible to have limits on the use of a specific model of these transportation tools. So, more research and work are still being done to avoid the major weaknesses of this main bloc. Firstly, the use of any electric vehicle is secure and safe, and secondly, it makes the battery autonomy of any electric vehicle better than others and allows for long distances for travelling.

If we concentrate on the vehicle autonomy problem, some works have appeared to present some solutions for enhancing vehicle autonomy. A few tactics focused on reducing the vehicle's body's aerodynamic impact in order to lessen the air's reactivity at elevated rates of speed. By reducing the vehicle's kilograms, a few scientists were able to conserve more energy during the traction phase [9]. The solutions were not stopped in this field; even electrical engineering was searched to develop more powerful traction motors that consume less power and are more rentable. Special AC machines were designed for this objective and have demonstrated good performance for this transportation tool [10, 11]. All of these solutions were classified as hardware solutions and needed a prototype design and consumption. Other software proposals were constructed to help create a better relationship between vehicle autonomy and vehicle efficiency. It contributes to the power management consumption from inside the vehicle. It helps find a better combination for this complex relationship between the needed power to turn the electric vehicle On and between increasing the vehicle autonomy without restricting the vehicle's driving mode. Various types of power management have been documented in scholarly works. Researchers were involved in the development of the electrical traction method. A few improved vector control topologies, also known as direct torque control topologies, were introduced to improve the traction machine's reaction and reduce power loss during the transition stages [12, 13]. Further methods were put forth to assist in controlling the phases of recharge and discharge in the hybrid vehicle models [14, 15]. These methods, which are based on smart control techniques, have shown improved battery life and an excellent return in terms of energy usage [16, 17].

Also, the solution, which is based on vehicle communication, was found suitable for exchanging information between cars, and then it becomes possible to have a large source of information for building a related vehicle database. This option was discussed in more than one source, as it is in [18, 19], where the exchanged database information has the related energy consumption data. These data will be organized and filtered to use only the energy information source for making a learning step, and then the related optimal drive cycle model that will be followed by the vehicle can be obtained. This operation will be repeated in each trajectory range [20, 21].

Based on the previous works, the present paper tries to use the benefits of smart cities to help get a better and optimum energy consumption form for any electric vehicle type. The exposed contribution can be classified as a power management tool for an electric vehicle. This work's contribution is to define better communication, what kind of information must be used, and how the information management method will be used. On the other hand, the outcomes of this novel power management method will be defined and explained so that it can be adapted for this kind of application. All of this work will be based on the benefits of smart cities.

In this way, the paper was formulated and composed of five sections. The first section presents an introduction, describing the state of the art and discussing the paper's contribution. In the next section, the studied prototype based on the electric vehicle model was defined and modelled using a mathematical equation. Next, the concept of an electric vehicle in a smart city was defined and explained in the third section. The main parameters and the essential variables are exposed inside the main objective function, which defines the overall mathematical problem. Then, the proposed power management concept is formulated in section four, and the related flowchart is built to know the contribution to the power management loop. Results and discussions were then exposed in the next section. The benefit of the exposed power management concept was cited. The future endeavours concerning this work were then discussed.

2 THE VEHICLE AND ITS POSSIBLE SENSOR TOOLS

Electric vehicles were developed in two models: total electrical vehicles (TEV) and hybrid electrical vehicles (HEV). At last we will find an electrical motor, which will be used as the main or reserve active motor. This is possible in the hybrid version [13]. The battery and the electronic power system are present in two versions of cars. The fuel tank and the ICE are present only in the hybrid version. The position of the electrical motor with the hybrid one gives the nomination of a series or parallel hybrid electrical vehicles [14]. The recent technology of connected vehicles, also known as smart cars, is equipped with advanced communication technologies that enable them to connect to other vehicles, infrastructure, and the internet. These technologies include a variety of sensors, such as cameras, radar, lidar, and GPS, which provide real-time data about the vehicle's surroundings. Cameras are used to detect and identify objects, pedestrians, and traffic signs. Radar sensors are used to measure the distance and speed of objects around the vehicle, while lidar sensors provide high-resolution 3D maps of the surrounding environment. GPS sensors are used to provide precise location data and enable the vehicle to communicate with other vehicles and infrastructure. Together, these sensors enable connected vehicles to communicate with each other and with the surrounding infrastructure, which can help improve safety, reduce congestion, and enhance the driving experience. Fig. 1 gives the concept of the connected vehicle and the type of basic information to be exchanged in the city [22]. It is important to mention that the vehicle's mathematical model is not the same whether the vehicle is on the road or not. If the vehicle is stopped, no forces exist, and then no power to be extracted is present; however, if the vehicle is in movement, many forces exist from the exterior, and this is in relation to the vehicle's speed [23]. Eq. (1) exposes the related energy expression based on the vehicle velocity v, which is supposed to be constant for a specific time of period 't'. This expression is based on vehicle-related constants such as vehicle weight, resistive torque, and frontal vehicle space, as shown in parameters A, B, C.

$$E_2 = \int_0^t \left(A \cdot v^2 + \left(B + C \cdot v \right) \right) \cdot v \cdot \mathrm{d}t \tag{1}$$

A, B and C variables are defined as it is exposed next.

A second energy equation model can be revealed in relation to the acceleration form. It is expressed in Eq. (2). It is mentioned that "a" is the acceleration ratio and "v" is the vehicle speed.

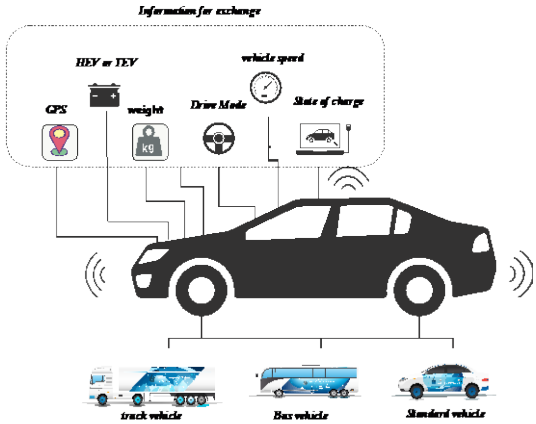

Figure 1 Needed information to be extracted from a vehicle

$$\begin{aligned} A &= \frac{1}{2} \cdot \rho \cdot A_f \cdot C_D \\ B &= C_r \cdot m \cdot g \\ C &= C_v \cdot m \cdot g \end{aligned} \tag{2}$$

$$\begin{aligned} E_1 &= \int_0^{v/a} \left(m \cdot a + A \cdot \left(a \cdot t \right)^2 + \left(B + C \cdot \left(a \cdot t \right) \right) \right) \cdot \left(a \cdot t \right) \cdot \mathrm{d}t = \\ &= \frac{1}{2} m v^2 + \frac{A v^4}{4a} + \frac{B v^2}{2a} + \frac{C v^3}{3a} \end{aligned} \tag{3}$$

Based on the previous related energy equations, the global energy consumption form can be expressed in Eq. (4). The resulting deceleration energy noted E_3 will be added. In this work, this quantity was supposed to be null.

$$E = E_1 + E_2 + E_3 \tag{4}$$

For such a drive cycle, where the vehicle stops can be n, and the vehicle speed is v, the related energy equation can be exposed as it is in Eq. (5).

$$\begin{aligned} E(v, n) &= (n+1) \cdot (E_1 + E_3) + E_2(v, n) = \\ &= (n+1) \cdot \left(\frac{1}{2} m v^2 + \frac{A v^4}{4a} + \frac{B v^2}{2a} + \frac{C v^3}{3a} \right) + \\ &+ \left(A \cdot v^2 + B + C \cdot v \right) \cdot \left(s - (n+1) \cdot \frac{v^2}{a} \right) \end{aligned} \tag{5}$$

3 THE CONCEPT OF CONNECTED VEHICLE (V2X)

3.1 Type of Sensors for the EV

The concept of a connected vehicle is related to what kind of sensors exist, and this variety of sensors is employed to ensure both safety and efficient energy management. These sensors serve as the eyes and ears of the vehicle, providing crucial data for real-time monitoring and control. One of the primary sensor types used in EVs is the proximity sensor, which aids in collision avoidance and parking assistance by detecting nearby objects and obstacles. Additionally, ultrasonic sensors are utilized for blind-spot detection and rear cross-traffic alert systems, enhancing overall safety during driving maneuvers. To optimize energy management, EVs rely on a suite of sensors such as accelerometers and gyroscopes to monitor vehicle motion and orientation, enabling precise control of regenerative braking and stability control systems. Furthermore, temperature and humidity sensors are integrated into battery packs to ensure optimal operating conditions, prolonging battery life and enhancing overall efficiency. Advanced driver assistance systems (ADAS) in EVs also incorporate cameras and LiDAR sensors for lane-keeping assistance, adaptive cruise control, and autonomous emergency braking, further bolstering safety on the road. By leveraging a combination of these sensor technologies, electric vehicles can not only deliver a safer driving experience but also maximize energy efficiency, contributing to a sustainable transportation ecosystem.

3.2 State of the Art About the Benefits of the Smart Cities

The smart city nomination was applied in urban areas, where different types of electronic equipment and sensors were used to collect data and information about the roads and people. The collected information can be stored in a big database, used and edited to make a prediction on a decision or for estimating some information in order to resolve an existing or forthcoming problem. Many uses for the benefit of smart cities appeared. For example, the transportation sector was benefitting from the advantages of smart cities, such as reducing the waiting time for the common transport buses or reducing road clutter. Also, the security sector benefits smart cities, where all cameras can be connected and centralized in one place, and it will be easy to define the suspect or the target to be followed. On the other side, the energy field has benefitted smart cities, where it is easier to predict the needed energy level each month or it becomes easy to manage the power from the source to the destination. The use of smart cities has demonstrated a great yield in many related sectors [24]. For example, in relation to the energetic yields, in Barcelona city in Spain republic, the integration of smart technology for managing power has demonstrated that for an area of 33110 m^2, the gas emission has been reduced by 1610 tCO_2/yr., where the energy demand was equivalent to 170 kWh/m^2/yr and was reduced to 92 kWh/m^2/yr. Similar to Spain, Cologne, Germany city, has reduced its CO_2 emission to 1844 tCO_2/yr. in a similar surface. Another example can be found in literature, which can prove the efficiency of this smart technology [25].

Even though the noted benefits of smart cities are very rare, it can be seen that the benefits for the transportation sector are major. Actually, the accident rate decreased; in relation to road safety, some statistics of injury accidents appeared between 2010 and 2020 in France. Actually, in this city, the number of smart technology, such as sensors, cameras and transmitters, has grown on the road, and this proves why the number of injured people after accidents decreased from 84461 in 2010 to 55836 in 2020. The statistics that were exposed were depicted on the website of the Interior Ministry of France. More examples exist in Shanghai, Stockholm and more than any country in the world.

Smart cities bring significant benefits to the transportation sector by enhancing mobility and transportation efficiency. One of the primary advantages of smart cities is that they use real-time data analytics to monitor traffic patterns and optimize traffic flow. This data is used to inform transportation planning, which can help reduce congestion and minimize travel time for commuters. Additionally, smart cities can leverage digital technologies to provide real-time information to commuters, such as traffic updates, public transit schedules, and availability of parking spaces. This leads to improved public transportation, as well as reduced carbon emissions and fuel consumption. By reducing traffic congestion and improving transportation efficiency, smart cities also promote economic growth by improving accessibility to businesses and increasing productivity. Overall, the implementation of smart city technologies in the transportation sector can bring significant financial and environmental benefits.

In relation to several safety-made research studies and found statistics, a smart city concept can reduce traffic accidents by more than 15% in one research study made in Barcelona by 2020. By the same ratio, it was found that if the smart city concept is composed and autonomous cars are used, it will be possible to reduce the accident factor. The study was made in Singapore [27]. A similar study, made in the USA, gave a traffic accident factor equivalent to 16%. All of these results have proven the importance of this fusion between the concept of a smart city and the transportation sector.

Actually, it is difficult to make a mathematical model for a smart city, as more variables and parameters can be inside the model. For example, variables related to various aspects of city life, such as transportation, energy consumption, waste management, and public safety, can be enough for having a similar model, but these variables might include data such as the number and type of vehicles on the road, including their fuel efficiency and average speed, the location and energy usage of buildings in the city, including data on heating and cooling systems and energy-efficient technology, the amount and type of waste produced by the city, including data on recycling rates and landfill usage.

The model might also include data on the city's population and demographics, as well as information on economic factors such as employment rates and tax revenues.

Once all of these data is collected, it can be used to create a mathematical model that simulates various scenarios and predicts outcomes based on different inputs. For example, the model might be used to predict the impact of introducing more bike lanes on traffic flow and emissions or the effect of upgrading the city's lighting systems on public safety [29, 30].

3.3 Database Structure Specification

At its core, this database is designed to handle a myriad of data types ranging from real-time traffic updates and weather conditions to vehicle telemetry and navigation instructions [31, 32]. Structured in a hierarchical manner, it comprises various layers, such as the raw data layer, processing layer, and application layer. The raw data layer aggregates incoming data streams from sensors, GPS systems, and other sources deployed across the road network. These data are then processed and analyzed in the processing layer, where algorithms decipher patterns, predict traffic flows, and identify potential hazards [33, 34]. Finally, the application layer disseminates actionable insights to connected vehicles, enabling them to adjust routes, maintain safe distances, and optimize fuel efficiency. This database structure not only enhances the driving experience but also lays the groundwork for future advancements in autonomous vehicle technology, promising a future of smarter, more connected roadways.

3.4 Vehicle to Database: Information Exchange

Recently, the communication between vehicles and external IoT equipment has reached a high level of security and road safety, and this was based on the activation of the relationship between the vehicle and the smart city concept. The benefit of this concept was found helpful for improving related services that have been impacted by road traffic. Using the benefit of the information, knowing it will be easier to have a faster delivery service, optimize trajectory and time, and then have an impact on the energy consumption factor [35, 36].

The principal objective of this study is to prove that the relationship between EVs and Smart cities will be able to improve vehicle autonomy. Actually, each vehicle has its energy consumption form in relation to the vehicle's internal and exterior situations [37, 38]. If more than one vehicle exists on the same road, it will be able to have a large information database that combines more than vehicle energy management experience. An optimal energy experience will then be produced by an optimization algorithm and shared to be profitable from the other vehicles on the road [39].

Fig. 2 gives the concept of the information exchange between vehicle and data. The idea is to share the information of a vehicle on a specific road. This information will be collected from thousands of cars that have crossed the same trajectory. All these details will be collected and stored on a Big Data Cloud; then, this information will be treated through a neural network algorithm to find the best and optimal solution for that trajectory [40, 41]. Fig. 3 shows the information type and exchange method in the corresponding algorithm. So, in a specific road trajectory defined by the departure and arrival points, it will be eligible to find vehicles of differnt types, weights, speeds and battery state of charge. All of this information will be organized in order to classify the vehicles by similar categories.

On the other hand, road specifications, such as maximum allowed speed, security level, slope types, and other information, will be selected as an identifier factor in the vehicle recommendation step.

All of this information must be stored in the database, and then it will be eligible to identify the new vehicle and classify it in the right category in relation to the selected road. So, the optimization algorithm will be executed, and it will be possible to have the optimal drive cycle method, which conducts a better energy experience.

The system initiates its interaction with a new entry by soliciting essential information about the car model, current vehicle position, and intended trajectory.

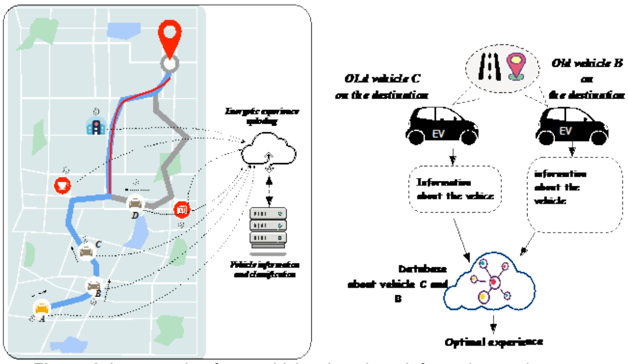

Figure 2 An example of two vehicles that share information on the same trajectory using the database on cloud

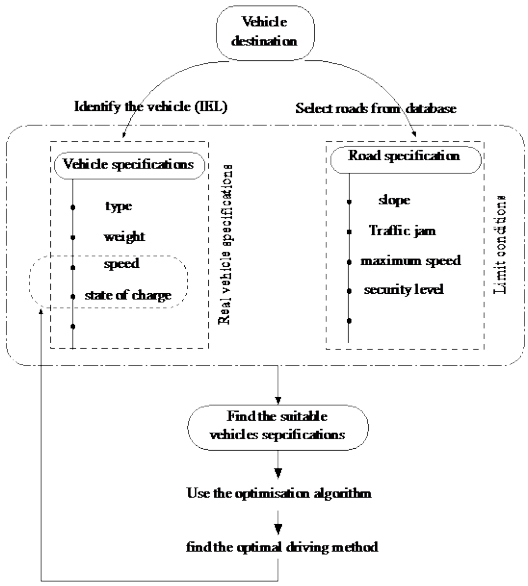

Figure 3 Information of vehicles shared in the cloud database

These details serve as fundamental data points for categorizing the vehicles appropriately within the database. Employing a predefined algorithm, the system meticulously compares the provided vehicle information with existing records stored within the database. Should similarities be detected between the current vehicle state and previously recorded scenarios, the algorithm proceeds to select the most optimal scenario from the available options. In instances where novel information is absent, the system undertakes database updates to reflect the new vehicle category and initiates a learning phase.

This iterative process ensures continuous refinement of the database, fostering the emergence of energy-optimal conditions for each vehicle entry. For hybrid vehicles, additional inquiries delve into energy consumption patterns encompassing fuel and electricity usage alongside the quantity of stored energy. Moreover, the system examines the vehicle's speed to comprehensively assess its energy dynamics. However, if critical variables such as energy consumption or speed data are missing, the vehicle's entry into the database is deferred until all requisite information is provided, ensuring the integrity and completeness of the database records.

3.5 The Learning Algorithm Discription

The protocol will manage the majority of the car-identified parameters into many vector inputs due to the large existing information from multiple sources, including multiple connected automobiles. The information vector presented in Eq. (6), gives the desired information of the pure electric vehicle number (x), where the information in relation to speed, battery state of charge and the vehicle load is mentioned respectively inside the vector.

$$input\ vector(x) = \begin{bmatrix} vehicle\ speed(x) \\ related\ voltage(x) \\ battery\ state\ of\ charge(x) \end{bmatrix} \tag{6}$$

$$output\ vector(x) = \begin{bmatrix} acceleration(x) \\ low\ voltage\ limit(x) \\ max\ voltage\ limit(x) \end{bmatrix} \tag{7}$$

On the other hand, inside the database, there is a ready recommended reference database that shows the desired trajectory and its best corresponding drive method. This reference vector will be the final output that will recommend the vehicle when needed. Fig. 4 explains this principle. Actually, an existing database, which contains all the previous information from a previous car on the same road, will be used as a source of information for the neural network, which can estimate the best driving method for the desired vehicle by giving the speed limits and the optimal drive method, as it is mentioned in the vector in the Eq. (6).

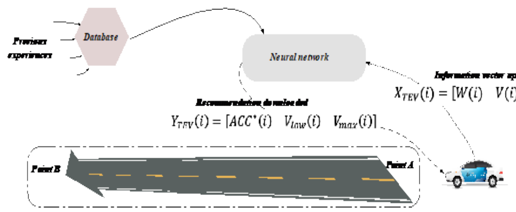

Figure 4 Vehicle vector information exchange

The proposed neural network controller/supervisor is made on a neural network architecture based on five input layers, two hidden layers and one output layer, using the sigmoid learning function.

The ideal issue that can express the objective function, in search for obtaining the optimal driving cycle, can be expressed in Eq. (8).

$$\min E(v, n) = f(a) \tag{8}$$

So, by controlling the acceleration ratio, it will be possible to reduce the level of energy use.

It is important to mention that the vehicle speed must not exceed the fixed safety speed limits defined by the majority of cars in the selected trajectory, as it is in Eq. (9). d_i^{start} and d_i^{end} are the initial and last points in the desired trajectory.

$$V_{limit} = \left\{ v_i \le v_i^{\max}, \text{ for } \left(d_i^{\text{start}}, d_i^{\text{end}}\right) \right\}, i \in \{1, 2, ..., n_l\} \tag{9}$$

Six linked cars will be used in our attempt to describe the working algorithm; five of the cars will build the database, and the rest will be as visitors who will request an optimal energy experience.

Assumedly, the trajectory for each automobile is the same. Fig. 5 shows that the learning system will use the data from the five existing cars. Initially, the algorithm will study those vehicles and attempt to produce the optimal energy- experience. When a new vehicle is present and asks for an optimal energy experience for driving in the desired trajectory, the learning system will search for the optimal experience and define the best driving method for the new car. Then, the algorithm will restart it and try to improve its database; the car data will be added to the database.

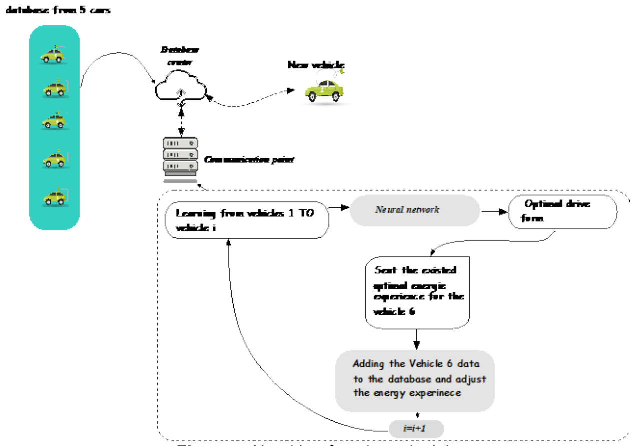

Figure 5 Algorithm function principle

Utilizing the stored data, the learning algorithm will deliver the optimal energy experience and, subsequently, the matching optimal driving technique. Those data will be revealed from all of the six used cars.

As an example of a presentation, the information about two different cars' acceleration forms and associated speed behaviours is displayed in Fig. 6 to show the situation of those parameters.

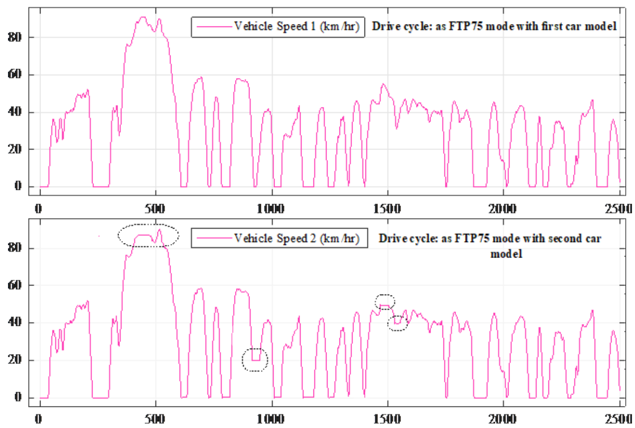

Figure 6 Two different acceleration forms from the cars in the database

As is shown in Fig. 7, the energetic experience of all four used cars in the database building is exposed. Approximately the four energetic experiences are the same, and only some change exists in the zoomed zones, which present the electric vehicle feedback in relation to the modified driven cycle form that was used for driving the vehicle. For example, for the first electrical vehicle, it seems that the driver conducted the vehicle in a different form than the other cases, especially in the instances between 200 and 300 seconds. For the other vehicles, each car was driven by a special drive method. All of these experiences and their SOC forms were used for the learning phase.

The regression plot of the training phase has demonstrated a good result, and it is clear that in the last four cases, the learning was approximately perfect. The maximum error per database source is equivalent to 8.9 points, as the neural output is equivalent to the initial input plus an error of 8.9 points. Fig. 8 shows the related results.

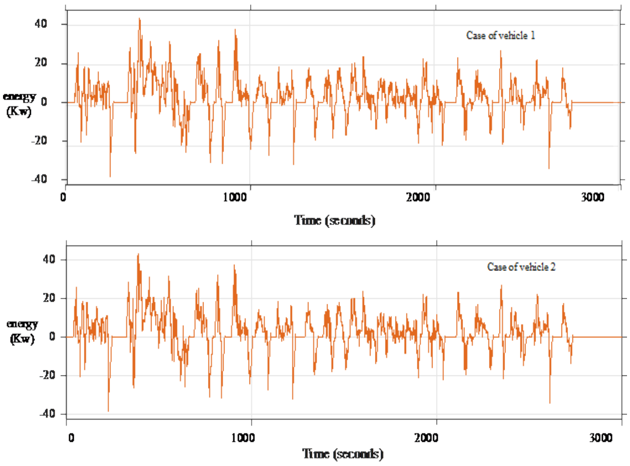

Figure 7 The related energy consumption form for the two used car

With these 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.

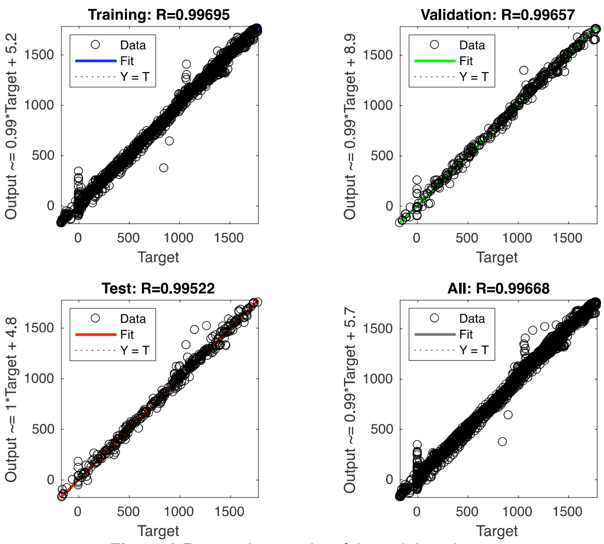

Figure 8 Regression results of the training phase

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 in a zoom section, for instance, 200 s to 340 s. As it is required to follow the energy consumption factor, Fig. 7 will expose the related energy consumption form for the given drive section as it is in Fig. 6. It can be seen that some difference exists in the energy curves for the three vehicle cases.

4 RELATED RESULTS DISCUSSION

The simulation prototype was based on an ensemble of the vehicles, as noted in Tab. 1. The total number of used cars is six, and only one needs assistance as the optimal trajectory form. After the corresponding neural bloc is created, the overall algorithm will be ready. It is easy now for any vehicle that asks for an optimal energy experience that has its needs. In Fig. 10 and Fig. 9, we expose the results related to the guest vehicle.

Table 1 Simulation specification

	Nbr of vehicle	Need Assistance
Vehicle on database	5	No
Vehicle not on database	1	Yes
Simulation time	2500 sec	
Drive cycle form	NFTP75	

The adaptability and the efficiency of the obtained neural network bloc will be tested on a new drive cycle form, as is in Fig. 9. This figure shows the optimal trajectory drive cycle obtained by the neural network and shows two different cars using the same trajectory with a different acceleration form. The related electrical motor speed form can be seen in the same figure, and less modification is present.

Fig. 9 shows the related SOC form for all the cases if the vehicle uses the optimal drive cycle model or if the vehicle uses its own drive cycle form. It can be seen that the SOC has a difference at the end, and if the optimal trajectory is followed, the final SOC will be higher than the other cases.

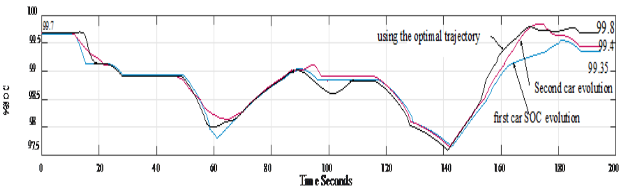

Figure 9 The better drive cycle selected by the algorithm

The associated battery level of charge for three different cars is shown in Fig. 10. While the others employed their own drive mechanism, one of them made use of the neural network's ideal drive cycle. It is evident that the three situations have distinct states of charge, particularly in the upslope. As it is for the period of 10, 50, 90, 150 and 180 seconds. This is a result of the improvement bloc's enforcement, which determined that in certain situations, a lower acceleration pitch is acceptable and does not have to be the highest. Similarly, for the other slopes.

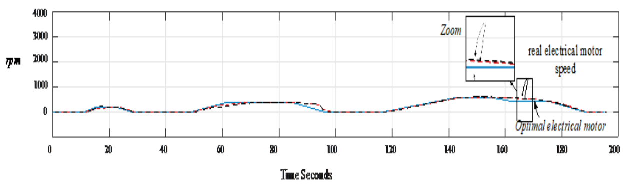

Figure 10 Battery state of charge for a car uses the optimal trajectory model and others without

The optimization algorithm has made its modification, and it is clear that at the end of the simulation period, the battery state of charge was kept at the same value as the initial battery state of charge. It is essential to mention that the car used model has the specification of energy regeneration in the down-slope road. This justifies why the battery SOC is going up in some periods.

Based on the given results, it is possible to compare the efficiency of the proposed energy management solution with the known solution as it is exposed in the literature. However, it is important to mention that the exposed EMS system is based on an external calculator that has information from outside the car. However, traditional EMS systems are inside the car and manage decisions in relation to the car's information. However, Tab. 2 tries to compare the benefits of this protocol with those of two standard EMS in the same trajectory. The given results were depicted using the Matlab Simulink application for a case of 1500 seconds and by using the FTP75 drive cycle. The EMS has taken into consideration the frequent stops on the road and has deactivated the regenerative mode. The battery state of charge has started from 70% for the three cases.

Table 2 Comparison between standard and proposed EMS

EMS protocols under FTP75		F_{SOC}	$°C\mu_p$	Δ_{soc}
Standard EMS	Fuzzy Rules	54%	50	16%
	Programming	52%	52	18%
Proposed EMS protocol		61%	30	9%

The results obtained were from three EMS systems, the fuzzy and the programming EMS and the proposed EMS system. It is clear that with the proposed EMS, the SOC has decreased by 9% from the other techniques, which have been characterized by a SOC reduction equal to 16 and 18%. So, if the vehicle follows an optimal drive method in the same trajectory, it will be more profitable if the EMS uses its standard outputs to manage the power consumption method.

5 FUTURE ENDEAVORS

The integration of Smart City concepts and IoT solutions holds immense potential for revolutionizing the transportation sector, promising enhanced efficiency, safety, and sustainability. By embedding sensors and connectivity into infrastructure, vehicles, and transportation systems, cities can gather real-time data on traffic flow, road conditions, and public transit usage. This wealth of information enables authorities to optimize routes, reduce congestion, and improve overall mobility. Additionally, IoT-enabled smart infrastructure can enhance safety measures by providing alerts for hazards and coordinating emergency responses swiftly. Moreover, with the advent of autonomous vehicles, IoT technologies play a pivotal role in enabling communication between vehicles and infrastructure, facilitating seamless coordination and navigation. Furthermore, by promoting the integration of various transportation modes through digital platforms and mobile applications, Smart City initiatives foster a more interconnected and accessible urban transportation network. Ultimately, the convergence of Smart City concepts and IoT solutions offers a transformative approach toward building efficient, sustainable, and user-centric transportation systems for the cities of tomorrow. It is important to mention that the robustness of the proposed EM concept must be tested by more than drive cycle mode, so this can be a great addition to this work in the future. On the other hand, this work can be extended by a better explanation of the possible and required frequencyof time changes in the data from the vehicles and the database. As the quantity of information will be enormous, this needs to be fixed and correctly studied. How to plan the next tests and validate the proposed concept seems to need to be clarified and discussed more. This is why it is mandatory to complete these tasks as a future endeavour of this work.

6 CONCLUSION

This work has shown a novel topology for energy management., which can contribute to increasing vehicle autonomy and global adoption of electric vehicles. The smart city concept served as the foundation for the suggested idea.. The concept, which needs to build a database for each vehicle, having the information from different sensors on the car and outside the car, will be organized and used in training steps for building a neural network algorithm which can find the optimum drive cycle method in each specific road condition. A multiple drive cycle form was used to construct the concept, which was then evaluated in a specific drive cycle example. According to the findings, the battery state of charge was improved by utilizing the neural network algorithm's recommended drive cycle form. The presented results were depicted for specific cases, and more tests can be applied in the future for other drive cycle models and various car conditions.

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