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Research Article

Review of Predictive Control Techniques Aimed at Optimal Management of Micro-Grid Energy Systems And Hybrid Electric Vehicles Using Fuel Cells

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ABSTRACT

The continuous migration of fossil technologies towards renewable technologies makes it necessary for researchers to focus their efforts on the modelling of the elements that make up these systems, considering the balances and power flows between them, to meet the energy and power requirements, and to consider the characteristics of the drive train elements and the grid elements. Similarly, the control techniques must consider cost functions that allow weighting the economic resources in the operational, maintenance and lifetime of the elements. This paper considers various speed and consumption profiles and the implementation of economic cost functions that weight operational limits with constraints.

Keywords: Predictive, Models, Power, Fuel Cell.

INTRODUCTION

The demand for the world's energy supply is increasing and will continue to increase due to rapidly changing demographic trends and global modernization. The International Energy Outlook projects strong growth in energy demand worldwide through 2040 **[1].** Total global consumption of traded energy is expected to expand by 57% over the period 2002-2025. In principle, this scenario argues for the need to intensify research on energy issues. We can say that there are two clearly marked contexts, and very differentiated according to the economic capacity and technological development in the countries. The *first context*, and being the majority in third world countries, in which it is still common to see that the majority of their electricity generation and their vehicle fleet is based on technologies that use fossil fuels. As far as industrial electricity generation is concerned, we find thermal plants, internal combustion engines, gas turbines, nuclear plants, among others. This type of technology, as expected, has certain characteristic problems in its operation and maintenance that must be solved, and in which research has been produced to improve them. Some problems are usually the amount of CH_4 and CO carbon monoxide emissions, the mechanical efficiency of the components (boilers, generators, exciters), the performance and efficiency of engines (at different points of operation), and aspects related to torque, power, and specific fuel consumption. As far as classic vehicles are concerned, they present problems around their efficiency and operation. Some problems already studied for this type of technology (injection engine only) are the amount of air/fuel mixture in the cylinders, torque control, ignition control (to improve the efficiency of the machine), preventing unwanted ignition processes from destroying the pistons and other parts of the cylinder (due to high pressure peaks), aspects related to thermal efficiency, analysis of combustion temperatures, and improving fuel efficiency. Several authors such as **[2], [3], [4], [5], [6], [7], have** dealt with the problems inherent to this type of technology, such as those mentioned in the previous paragraphs and belonging to the first context.

A *second*, more recent context, on which this article will be based, is the gradual replacement of these fossil technologies with clean technologies and renewable energy sources. The main issues underpinning the growth of renewable energy are the current fossil-fuel-regulated energy situation, affected by the depletion of fossil fuel reserves, global warming, energy security issues, and rising energy costs. The concepts of renewable energy grids and hybrid/electric cars then begin to appear, which will be explained in more detail in the following subsections. Some solutions during the transition from context one to the present day of context two, were for example the design of lighter and more efficient vehicles, which do not require high consumption of both fuel and electricity, as well as the individual generation of some solar, wind or other means of clean generation plants. Next, the problems and trends of technological and research development in the fields of application of vehicles and smartgrids will be analyzed, to later review the control technique that will be used in the development of this article.

1.1. Materials and Methods, areas of application:

1.1.1. Vehicles

According to **[16]** the problem of energy depletion and environmental pollution are the main stimuli for the transition from scenario one to two already mentioned above. Based on this, injection vehicles are gradually being replaced by hybrid or purely electric vehicles. According to **[15],** it is expected that by 2020 approximately 18% of new vehicles sold in Europe, and 7% in the US, will be sold in the United States. In the US, they will be HEV and 8% and 2%, respectively for pure electric vehicles. It is clear that the development of control techniques for EVs must be the direction of the automotive industry. Key control topics mainly include torque management in HEVs, the storage element management system for EVs, motor drive technology and energy recovery control. Within the development of hybrid vehicles, fuel cells have a high efficiency compared to other energy conversion systems, so some studies show that they are more efficient in the automotive field than those powered by gasoline as the main fuel. In addition, unlike internal combustion engines, the fuel cell's efficiency is also high at partial loads. In standard driving cycles, in urban and suburban areas, most of the time the vehicle is demanding a small fraction of the fuel cell's rated power according to **[20].** Therefore, a vehicle that has a fuel cell as its main source of energy will be working most of the time at high efficiencies. At the same time, with the use of hydrogen in a direct fuel cell, the problem of local emissions in densely urban areas can be eliminated. So, with the new vehicle electronics, some more complex actuators are included in control systems, which causes the increased degrees of freedom and complexity of dynamic coupling. As a result, the design and calibration of control systems is becoming more and more complex, bringing new challenges to the application of control theory and methods. Under this preamble we can define a modern vehicle as systems composed of different energy sources (some bidirectional, such as batteries and supercapacitors, the same ones that deliver energy and at the same time are capable of storing it), and some charges (that generate movement such as the traction system). The aim is for the traction system to follow a driving profile (unknown a priori) and a load consumption profile, minimising energy consumption while also reducing emissions. An important aspect to take into account is the desired speed profile. In some scenarios it is possible to have an estimate of the route to be made and the consumption of the loads to be powered, in these cases this estimate can be used to improve the energy management of the system.

There are several configurations for generating electricity in the vehicle. Authors such as **[13], [14], [15] and [16]** show the main ones and their problems in terms of simulating and modeling them. Figure 1 shows the priority parts that can be considered for the mathematical formulation and subsequent description of the existing problem. It is also important to take into consideration the fraction of recoverable energy from braking, which will be called regenerative braking and will be analyzed later in this work.

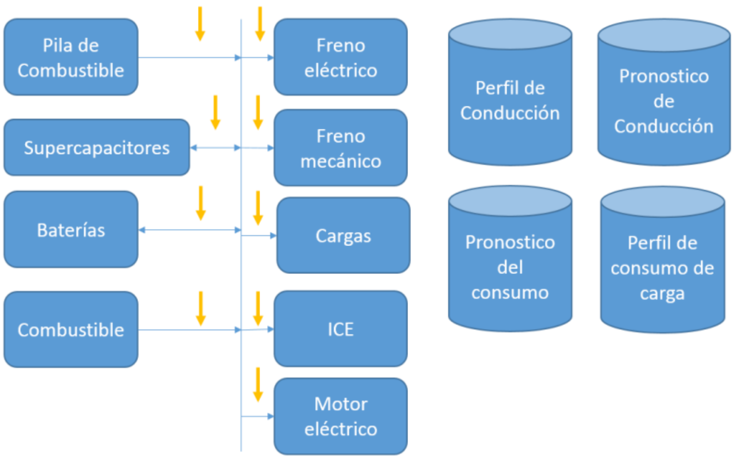

Fig. 1. Elements to consider as part of a vehicle model. In original language Spanish

In **[8],** two ways to configure a hybrid electric propulsion system are shown, in parallel and series. Figure 2 and Figure 3 show the parallel configuration and the serial configuration respectively. In the first case, the internal combustion engine (ICE) and the electric machine (EM) are mechanically coupled to the vehicle's axle unit. The total torque supplied is the sum of the individual torques. Another advantage is that the EM can also function as a generator to recover braking energy. For the second case, it is characterized by the absence of a mechanical connection between the ice and the wheels. Instead, the wheels are fully powered by an EM without the need for a transmission. The MS obtains electricity from a generator coupled to the ICE. This propulsion system gives a choice of ICE speed and torque, regardless of the speed of the vehicle.

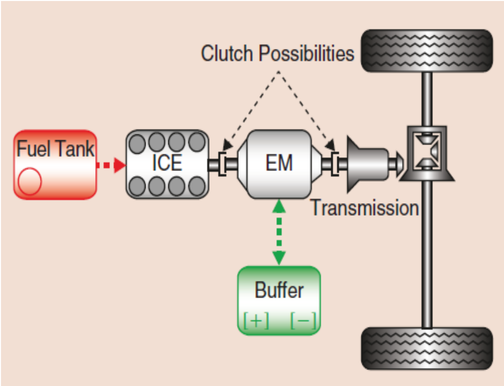

Fig. 2. Parallel configuration of hybrid electric drive systems for vehicles.

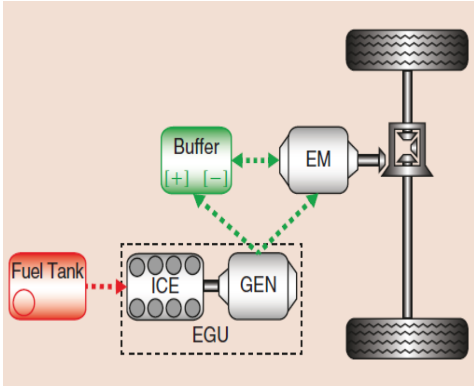

Fig. 3. Series configuration of hybrid electric drive systems for vehicles.

1.1.2. Migro-grid environments

Within the aforementioned scenario 1, it was common to observe that there were power generation plants that were always operating at their maximum capacity, while there were some of quick entry/exit such as internal combustion engines, which supply consumption at the so-called peak hours. These engines that run on diesel, fuel oil, among other similar types of fuel, often due to poor maintenance generate a considerable amount of pollution, which is not properly regulated in some countries. At the same time, it has efficiency problems, damage to the gas venting systems and other mechanical problems that make its operation not the most optimal. Therefore, one of the main objectives of making or implementing a smarter energy grid is to improve the efficiency and sustainability of the electricity generation infrastructure, which allows cheaper energy generation, with higher levels of reliability than the current ones, and that takes into account the issue of environmental care. To this end, the need is created to maintain a balance in accordance with what is generated and what is consumed, to avoid drastically increasing generation at certain times of load demand. This implies that it is very common to find hierarchical levels of control, which will be analyzed later, for local control and for the management of the complete energy system. [**14]** shows that renewable sources of energy and systems for distributed generation are concentrated in three important programs, the first being electricity generation based on renewable sources such as solar, photovoltaics, biomass, biogas, wind generation, geothermal energy and hydroelectric energy, the second, the generation of electricity and heat through renewable energies (CHP). and the third, the increase in efficiency and the use of heat generation pumps in combination with CHPs for residential uses, for example.

Another important aspect is the feasibility of integration and real-time communication of the new systems, with other types of existing systems, decentralized generation, energy buses, storage capacity and form, as well as the optimal management of the subsystems depending on global needs. This is supported by the most accurate climate predictions that occur over time. Authors such as **[8], [9], [10], [11], [12], among** others, have begun to develop variants for the use of new technologies to replace those that use fossil fuels. For this work, environments with distributed generation and consumption will be used, where there are different energy sources whose production is fixed by environmental conditions such as wind turbines and photovoltaic panels. In addition to these sources, there are other types of fuel cells or diesel machines that allow the required energy to be generated at any time, as mentioned above. Figure 4 shows graphically some elements that will be considered in the analysis and study of the microgrid environment later.

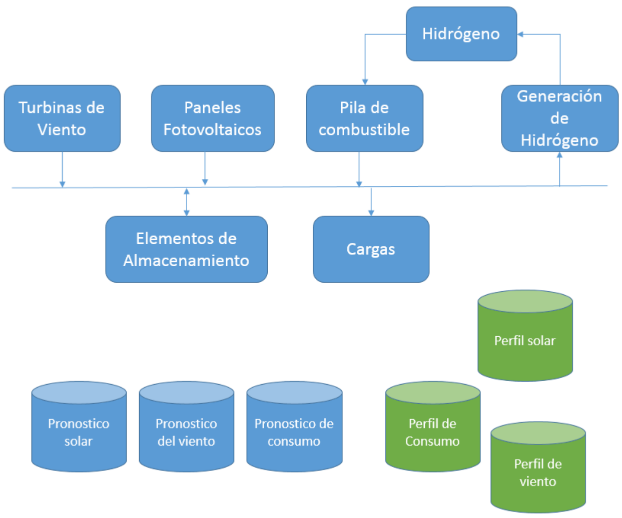

Fig. 4. Elements to consider as part of a smartgrid. In original language Spanish

Another consideration to take into account is that energy consumption needs are time-dependent. In addition to the sources and loads, there are energy storage (or micro storage) elements that allow energy to be temporarily stored (batteries, fuel cells, hydrogen generation). Nowadays it is possible to have predictions of environmental conditions that allow us to have an estimate of the energy generated by each of the sources. Similarly, and based on historical data, it is possible to have estimates of the consumption of the loads. The objective of the energy management system is therefore to manage energy resources in such a way that the energy available at all times is used to the maximum and the consumption of fossil energy sources is minimised. Authors such as **[17], [18], [19] and [20]** have analyzed in detail the architecture and functionality of Smartgrids.

1.1.3. Control MPC

According to **[13],** the main objectives of control systems for vehicle applications are to achieve maximum fuel economy, reduce emissions, make the system operate at minimal cost, and obtain efficient performance. There are several techniques that have been widely studied such as fuzzy rule-based methods, deterministic rules, optimization-based strategies, and real-time strategies **[10], [9], [9], [7].** We can also say that an a priori analysis of the hierarchical control of the system as such, we can consider the local controllers as a sublevel of control, since they are seen as necessary constraints for operation, which we will analyze in more depth in the section on the state of the art. As a first count, we can say that for this type of system, control algorithms are required that allow optimal management of them in a way that optimizes both generation and storage/transport strategies. It is therefore proposed to study economic predictive control as a possible methodology to develop optimal management. The economic predictive control technique generalizes the standard predictive control technique by including in the objective function criteria that go beyond the traditional criteria of setpoint or control effort tracking, such as production/transport costs, security of supply guarantees and smooth operation of the actuation elements. By incorporating control criteria different from traditional criteria into the cost function, the fundamental properties of the control law such as stability, convergence, among others, must be restudied to see under what conditions they are guaranteed both in cases of nominal operation and in the presence of uncertainty (robustness).

1.1.3.1. Control EMPC

The goal of most advanced control systems today is to guide a process to a target set point quickly and reliably. Searching for the optimal steady-state reference point is usually done by some other information management system that determines, among all steady states, which is the most profitable. However, this hierarchical separation of information and purpose is no longer optimal or desirable. A proposed alternative is to take the economic objective directly as part of the control system's function. For the controller to directly optimize the economic performance of the process in real time, instead of tracking to a setpoint **[102]**. According to **[11],** model-based predictive control (CPM) can be defined as a control strategy that is based on an internal mathematical model of the process to be controlled, better known as a prediction model. This model is used to predict the evolution of the variables to be controlled during a specified time interval; In this way, the future control variables "u" can be calculated to ensure that in that horizon the control outputs "y" converge to their respective reference values. This optimization is carried out within a prediction horizon, with the model initialized at the beginning of the prediction horizon from the measurements (or estimation of the state of the system). This optimization is executed in each sampling period "k" **[7]**, as illustrated in Figure 5. The control signal to be applied to the process is obtained by solving an optimal control problem of a criterion, cost function (or objective function) in an open loop within a finite control horizon and in each sampling period k, subject to constraints given by the operational characteristics of the system, or by the physical limitations of its components **[10]**. As a result of this optimization, a sequence of optimal control signals is obtained in each sampling period, of which only one of them is applied to the process and the prediction horizon is shifted to the next instant of time before starting the optimization again using the sliding window principle **[6]**.

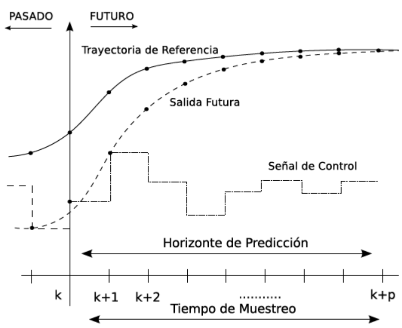

Fig. 4. MPC Control Working Principle

1.1.3.1.1. State Space

A dynamical system expressed in state space has the following structure for the first sampling time

$$x(k+1) = Ax(k) + Bu(k) + B_p d(k) \qquad (1)$$

$$E_u(k) + E_d d(k) = 0 \qquad (2)$$

where:

$x(k) \in R^n$ it is the vector of states corresponding to the energy of the different sources considered. By means of power measurements, they are all considered measurable.

$u(k) \in R^m$ It is the input vector that is defined by the power that each of the sources is capable of supplying to the system.

$d(k) \in R^p$ it is the vector that contains the perturbations measured in the system, referring to friction.

A, *B*, and *Bp* are the state matrices and *E* and Ed are matrices of adequate dimensions and signs that describe the equilibrium relationship between the states.

In **[7],** the control formulation of the Predictive Model is extensively described

1.1.3.1.2. Control Restrictions

The operating constraints of the control signals are set by dimensions

$$\text{umin}(k) \leq u(k) \leq \text{umax}(k) \qquad (3)$$

That can be included in the MPC control optimization problem as inequality constraints

$$\text{umin}(k) - u(k) \leq 0, \qquad (4)$$

$$u(k) - \text{umax}(k) \leq 0 \qquad (5)$$

Or, in matrix form such as

$$\begin{bmatrix} -1 \\ 1 \end{bmatrix} u(k) + \begin{bmatrix} u_{min} \\ -u_{max} \end{bmatrix} \leq 0 \qquad (6)$$

Where the first term is the matrix formed by two alternating sign identity submatrices whose size is given by the number of manipulation signals "*mi*", while the second term is the vector formed by the minimum and maximum limits that define the constraints on the manipulation variables and that are ordered alternately. If we call *the* first term F, and *the* second term, f, and generalize for a prediction horizon of sampling instants and "*my*" manipulation signals, it can be expressed as

$$F\mu + f \leq 0 \qquad (7)$$

1.1.3.1.3. Status Restrictions

For state constraints, we can limit them as shown in

$$\text{xmin}(k) \leq x(k) \leq \text{xmax}(k) \qquad (8)$$

And include them in the optimization problem in a similar way to (5).

1.1.3.1.4. Cost Function

A multiobjective square linear cost function is used, because the constraints are defined in the form of inequalities and in a certain way fit this type of optimization. The main objective of a hybrid renewable energy system is to make the most of the available energy and meet the demand requested by the loads, while optimizing the storage or provision of excess or deficit energy that is present during each instant of time. The cost function is the translation of control objectives into a mathematical expression. In classical predictive control, deviations in future control actions from the suitably defined reference path are penalized. In EMPC predictive control applied to energy management systems **[13].**

$$min \int J \sum_{i=o}^{Hp-1} f_1(k+i \vdots k) + \sum_{i=o}^{Hp} f_2(k+i \vdots k) + \sum_{i=o}^{Hp-1} f_3(k+i \vdots k) \quad (9)$$

Where J is the combination of (10), (11) and (12), defined by:

$$f_1(k) = w_\alpha\big(\alpha_1 + \alpha_2(k)\big)u(k)\Delta t \quad (10)$$

$$f_2(k) = \epsilon(k)^T W_x\, \epsilon(k) \quad (11)$$

And $f_3(k) = \Delta u(k)^T W_u \Delta u(k)$ (12)

Where are the vectors, the first fixed and the second as a function of time, associated with the energy cost of the problem to be formulated. , is the weight given to the cost function is defined as the penalty value of the soft constraints related to the safety values of the state of charge of the energy storage elements. It is a matrix of weights associated with these penalties. For smooth control, we define it as the vector of variations in the control signal and the matrix of weights associated with the control actions. The formulation of the optimization problem and its solution by quadratic programming using CPLEX/TOMLAB are explained in detail in $\propto_1$ y $\propto_2$ $w_\propto \epsilon(k) W_x \Delta u(k) W_u$ **[8]**.

Then, f1(k) minimizes the economic cost of the network, taking into account the production costs for the elements of the energy bus, which are taken in a weighted manner for each of the control actions. Then f2(k), is the performance index of the charging and discharging state of storage devices. Finally, f3(k) minimizes variations in control signals.

If we take into account equation (1), and say that we have "n" state variables, mi control signals and mp perturbation signals, they are expressed as shown in (13).

$$x_n(k+1) = A_n x_n(k) + B_m u_m(k) + B_p d_p(k) \quad (13)$$

Where the dimensions are for A of nxn, for Bu of nxm and for Bp of nxp. If we analyze equation (13) at the second sampling instant, we will have equation (14).

$$x_n(k+2) = A_n x_n(k+1) + B_m u_m(k+1) + B_p d_p(k+1) \quad (14)$$

Replacing (14) in (13), we have (15).

$$x_n(k+2) = A^2{}_n x_n(k) + A_n B_m u_m(k) + A_n B_p d_p(k) + B_m u_m(k+1) + B_p d_p(k+1) \quad (15)$$

Finally, if we take Hp as the sampling time, we will have the system represented below:

$$x = \begin{bmatrix} x(k+1) \\ x(k+2) \\ x(k+3) \\ \vdots \\ x(k+H_u) \\ \vdots \\ x(k+H_p) \end{bmatrix} \quad \vartheta = \begin{bmatrix} A \\ A^2 \\ A^3 \\ \vdots \\ A^{H_u} \\ \vdots \\ A^{H_p} \end{bmatrix}$$

$$\nabla = \begin{bmatrix} B & O & O & \cdots & O \\ AB & B & O & \cdots & O \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ A^{H_u-1}B & A^{H_u-2}B & \cdots & \cdots & B \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ A^{H_p-1}B & A^{H_p-2}B & \cdots & \cdots & \sum_i^{H_p-H_u} A^i B \end{bmatrix} \quad U = \begin{bmatrix} u(k) \\ u(k+1) \\ u(k+2) \\ \vdots \\ u(k+H_u-1) \end{bmatrix}$$

$$\gamma = \begin{bmatrix} B_p & O & O & \cdots & O \\ AB_p & B_p & O & \cdots & O \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ A^{H_u-1}B_p & A^{H_u-2}B_p & B_p & \cdots & O \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ A^{H_p-1}B_p & A^{H_p-2}B_p & A^{H_p-3}B_p & \cdots & B_p \end{bmatrix} \quad D = \begin{bmatrix} d(k) \\ d(k+1) \\ \vdots \\ d(k+H_u-1) \\ \vdots \\ d(k+H_p-1) \end{bmatrix}$$

Where finally the matrix expression of the system for the determined prediction horizon is given by (16).

$$X = \vartheta + \nabla u + \gamma D \qquad (16)$$

RESULTS.

The aim will be to model a system (vehicle) that has a fuel cell as its main energy source, and batteries and supercapacitors as energy storage elements. With these elements, and taking advantage of part of the energy provided by braking, a given speed profile will be followed. In the case of this work, the NEDC speed profile will be used. According to **[3]**, there are both urban and highway driving profiles. Some of them are the Urban Driving Cycle (UDC, also known as ECE-15) and EUDC (Extra Urban Driving Cycle). The ECE cycle is characterized by low vehicle speed, low engine load, and low exhaust gas temperature. The Extra Urban Driving Cycle (EUDC) simulates the conditions of driving on the road. The top speed of the EUDC is 120 km/h. The NEDC contains four UDC segments, and one from the EUDC. In [**8**], the equations that model the vehicle configurations shown in Figure 2 are presented, as well as the models of the individual components described in Figure 3. Below we will briefly describe the elements that make up the system.

4.1. System Elements

4.1.1. Vehicle Kinetic Energy

The energy balance will be made around the energy that the vehicle needs for its movement. To describe the model, it is necessary to take into account that there are dissipative forces, such as air resistance and resistance to slipping. The power required for the movement of the vehicle, Pmov, is deducted from the kinetic energy stored in the vehicle (Ev), according to **(1).** The dissipation power Pdis depends on the speed of the vehicle, and the dissipation force, according to **(2).** Pv is the total power required to produce the displacement of the vehicle and is related to the two potencien mentioned above, according to **(3).**

$$Ev = \frac{1}{2}mv^2 = \dot{Ev} = mv\dot{v} = Pmov \qquad (1)$$

The dissipation of the vehicle is

$$f_{dis}(v) = \propto + \beta v + \gamma v^2 \rightarrow Pdis = vf_{dis}(v) \qquad (2)$$

The power required by the vehicle for its movement is:

$$Pv = Pmov + Pdis, Pdis > 0 \qquad (3)$$

Where v is the given velocity and its future values are unknown in principle

4.1.2. Supercapacitors

In **[9],** it is mentioned that it is possible to power the vehicle and follow a certain driving profile only with the fuel cell, but due to the slow dynamics of the fuel cell, it is better to place storage devices such as the battery or supercapacitors for the particular case of this work. Supercapacitors have a high specific power, and they can deliver large amounts of instantaneous power unlike batteries that are slower. So the modeling of this storage device must meet equations (4), (5), and (6).

$$E_{sup} = \frac{1}{2}Cv^2 = \dot{E_{sup}} = Cv\dot{v} = P'_{sup} \qquad (4)$$

In practice to obtain as a higher power, PP'_{sup}sup must be calculated as follows due to the losses:

$$P_{sup=}\eta\ \eta < 1(v, P'_{sup})P'_{sup}, \qquad (5)$$

On the condition of:

$$v_{min} < v < v_{max}, p_{min}^{sup} < p < p_{max}^{sup} \qquad (6)$$

Where C is the capacitance, v is the voltage, and Psup is the resultant power.

4.1.3. Batteries

In **[5],** a combined method of charging elements between super capacitors and batteries is presented. The state of charge (SOC) is defined as the available capacity of a battery relative to the nominal capacity. Is represented as a percentage of a full load reference. The battery is given the same treatment as the Supercapacitors and its behavior is modeled in (7) and (8).

$$SOC = \frac{E_{bat}}{E_{bat}^{max}} \qquad (7)$$

On the condition of:

$$SOC^{min} < SOC < SOC^{max}, p_{min}^{bat} < p_{bats} < p_{max}^{bat} \qquad (8)$$

4.1.4. Energy recovered from the Brake (Regenerative Braking)

An important aspect to consider is the energy that can be recovered from regenerative braking, which depends on the driving profile and speed to be used, being greater in the urban area, as it has more traffic signage that allows constant braking. It is important to indicate that the amount of energy recoverable for the system depends on the supply capacity of the storage elements, so the rest must be dissipated in the braking itself. The amount and time that braking lasts is also important. Then the braking power must be restricted by (9).

$$\boldsymbol{P_{brake} < 0} \qquad \textbf{(9)}$$

4.1.5. Fuel Cell

Fuel cells have a high efficiency compared to other energy conversion systems, so some studies show that they are more efficient in the automotive field than those powered by gasoline as the main fuel. In addition, unlike internal combustion engines, the FC efficiency is also high at partial loads. In standard driving cycles, in urban and suburban areas, most of the time the vehicle is demanding a small fraction of the fuel cell's rated power according to [96]. Therefore, a vehicle that has a fuel cell as its main source of power will be working most of the time at high efficiencies. At the same time, with the use of hydrogen in a direct fuel cell, the problem of local emissions in densely urban areas can be eliminated. Equations (10) and (11) show the modeling of the power requirements given by the fuel cell for the system.

$$P'_{fc} = f(H), P'_{fc} > 0 \qquad (10)$$

$$P_{fc} = \delta(\cdot)P'_{fc} \qquad (11)$$

4.2. State Space

In **[7] and [8],** linear models analogous to the case of the vehicle are described, according to equations (18) and (19).

$$x(k+1) = Ax(k) + Bu(k) + B_p d(k) \qquad (18)$$

$$E_u(k) + E_d d(k) = 0 \qquad (19)$$

Where:

$x(k) \in R^n$ Rn is the vector of states corresponding to the measurements of power, and they are all considered measurable.

$u(k) \in R^m$ It is the input vector that is defined by the power that each of the sources is capable of supplying to the system.

$d(k) \in R^p$ It is the vector that contains the perturbations measured in the system, referring to friction.

A, B, and Bp are the state matrices and E and Ed are matrices of adequate dimensions and signs that describe the equilibrium relationship between the states. The state-space system will be as described in equations (20), (21), and (22).

$$P_{sup} = \dot{x_1} \rightarrow x_1(k+1) = x_1(k) + P_{sup} \qquad (20)$$

$$P_{bat} = \dot{x}_2 \rightarrow x_2(k+1) = x_2(k) + P_{bat} \qquad (21)$$

$$P_{fc} = \dot{x}_3 \rightarrow x_3(k+1) = x_3(k) + P_{fc} \qquad (22)$$

Then the model is described as follows in the state space shown in (23):

$$\begin{bmatrix} \dot{x}_1 \\ \dot{x}_2 \\ \dot{x}_3 \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ x_3 \end{bmatrix} + \begin{bmatrix} 1 & -1 & 0 & 0 & 0 \\ 0 & 0 & 1 & -1 & 0 \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} u_1 \\ u_2 \\ u_3 \\ u_4 \\ u_5 \end{bmatrix} + [0] \qquad (23)$$

Where:

$u_1 = P_{cargabat}; u_2 = P_{descargabat}; u_3 = P_{cargasup}; u_4 = P_{descargasup}\ u_5 = P_{fc}$

The equilibrium of the system is given by the vector Eu, shown in (24).

Eu = [-1 1 -1 1 1 -1] (24)

4.1. Restrictions

$$Pv = P_{brake} + P_{sup} + P_{bat} + P_{fc} \qquad (12)$$

The parameters to be used for the driving profile are those shown in Table 2.

Number	**Value**	**Unit**
Air density	1.2	kg/m3
Gravity	9.81	m/s2
Coefficient of resistance to movement	0.02	s/u
Vehicle drag coefficient	0.33	s/u
Powertrain Efficiency	0.8	s/u
Motor efficiency	0.9	s/u
Generator Efficiency	0.9	s/u
Front area of the vehicle	2.13	[m2]
Transmission coefficient	6.066	s/u
Vehicle mass	1185	[kg]
Rated Motor RPM	14000	[1/min]
Maximum machine power	49000	[W]
Wheel Spoke	0.291	[m]
Power consumed by auxiliary systems	400	[W]

Table 2. Parameters used in the NEDC profile.

The main parameters used for storage items are those shown in Table 3.

Name	**Value**	**Unit**
Maximum Supercapacitor Energy	1625	[KJ]
Maximum battery power	500	[KJ]

Table 3. Parameters used for the storage system

4.2. Simulations

The speed profile of the NEDC driving cycle is shown in Figure 1. As mentioned above, power flows will be used as control signals.

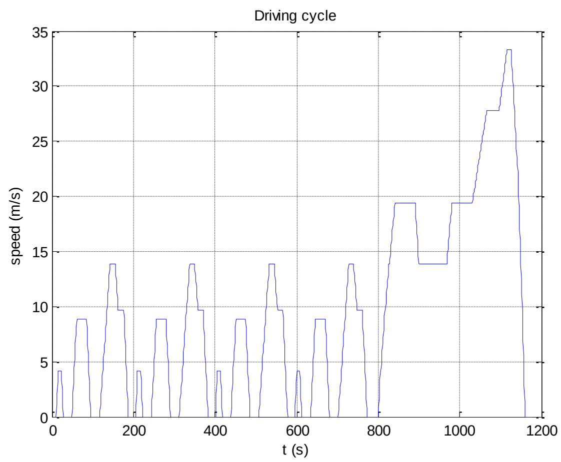

Fig. 1. NEDC Driving Cycle Speed Profile

The driving profile used allows us to have the speed as data and therefore derive the acceleration of the system as known values at all future instants of time. Therefore, as mentioned in **(1),** we can have the kinetic energy of the system, and the power provided by the kinetic energy. Of the power vector, the positive part or the values above zero, represent the part that contributes the kinetic energy in power, while the negative part or the values below zero, are the magnitudes that can return as power generated by the energy. As already mentioned and studied in **(3),** for the vehicle to be able to move, it must at least overcome the rolling force, the friction of the air and the energy necessary for movement (part of the kinetic energy). So, the total energy that is to be recovered is the sum of these three. Figure 4 shows in blue the negative part of the values of the power generated by the kinetic energy, or what can be returned from it; in green the power necessary for movement and in red the energy necessary to overcome air and bearing friction.

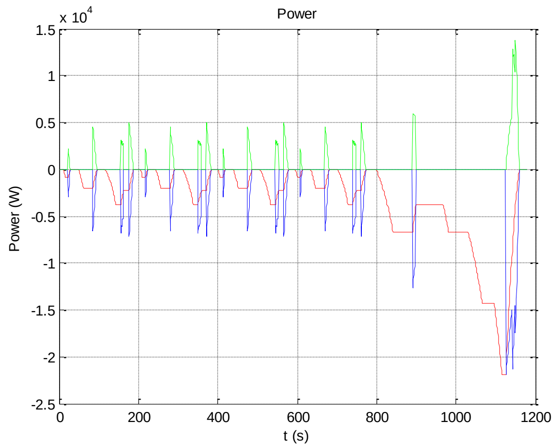

Fig. 1. Energy balance of a vehicle following the NEDC profile

The rate of recoverable energy over that contributed is 14.21%. Once the system is placed on the controller, the demand that is asked of the system with its primary source and storage systems is shown in Figure 1.

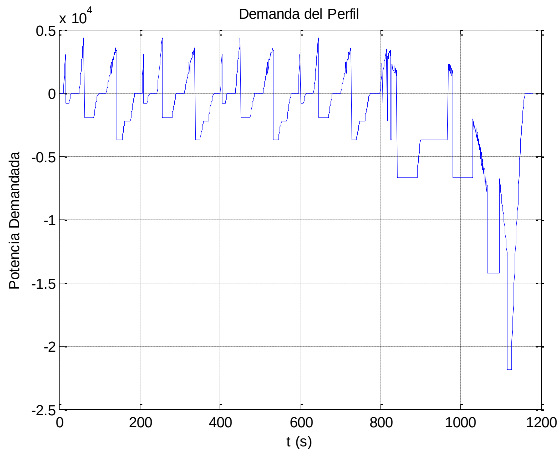

Fig. 1. Power Demand to Follow the NEDC Profile

Three simulation scenarios have been taken into account, with a prediction horizon of 10 units and a sampling time of 1 second. Figure 1 shows the power delivered by the system, the same as comparing it with the previous graph, it is exactly the same, so what the profile demands for the movement is met.

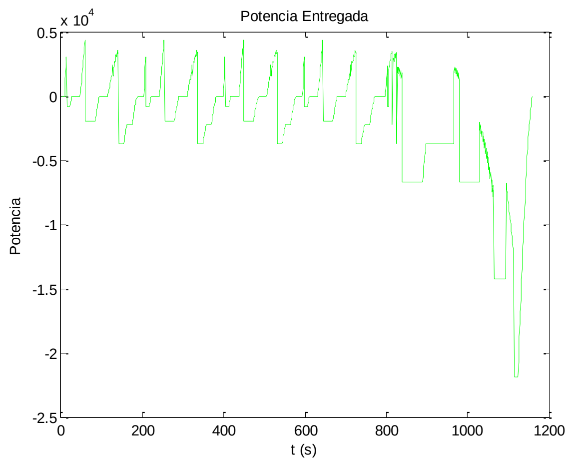

Fig. 1. Power delivered to follow the NEDC profile

The first scenario is when for the EMPC all the generation and storage sources that contribute to the system are cheap, that is, there is no weighting for any of them. 600 samples will be worked on for simulation. Figure 1 shows in green what the battery absorbs from the battery and from regenerative braking, in blue what the battery contributes to the system at times when power is demanded; yellow shows what the supercapacitor is capable of taking from the source and regenerative braking, while magneta shows what the supercapacitor is capable of giving to the system when it requires generating power; the contribution of the fuel cell is shown in black and the demand of the system is shown in red.

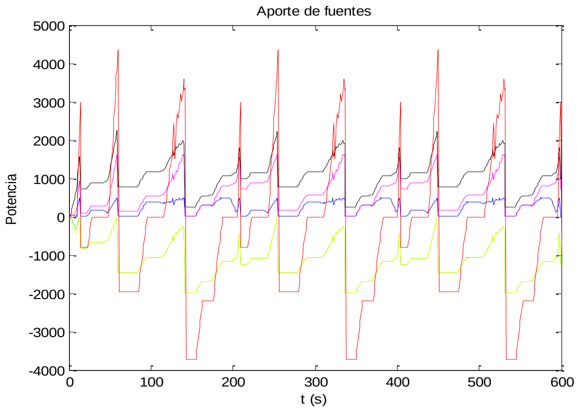

Fig. 1. Simulation of scenario 1.

In scenario 2, the fuel cell is made a very cheap source of generation, while the control signals that have to do with the contribution of storage sources to the system are made very expensive. The sources are allowed to be charged so that they take advantage of the energy given in braking. As in the previous case, the energy provided by the battery is seen in black.

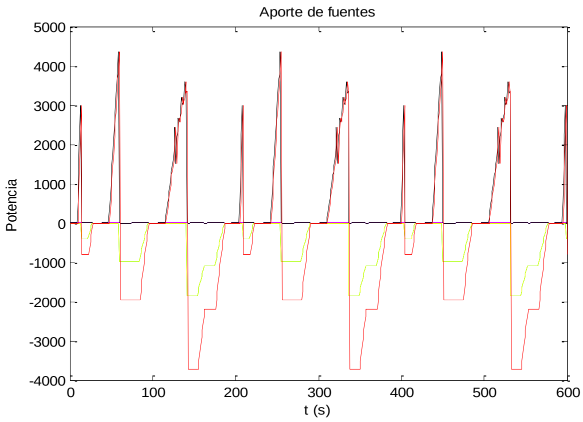

Fig. 1. Simulation of scenario 2.

In scenario 3, we make the fuel cell an expensive source in terms of generation, while the power provided by the other sources is cheap. As for the other cases, in green and yellow are the loads of the storage elements, in magneta and blue what they deliver in power to the system, in black the power of the battery and in red the demand. Figure 1 shows the simulation of this scenario.

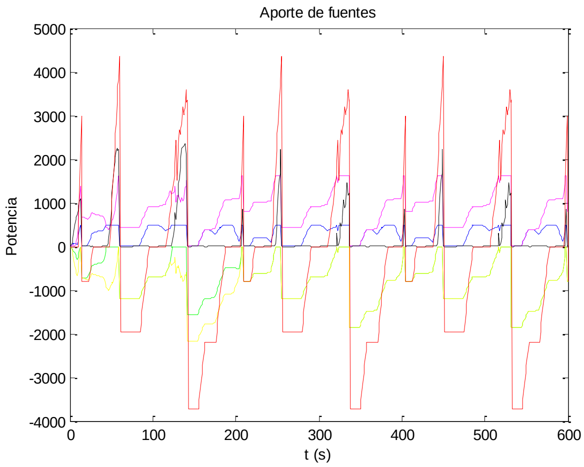

Fig. 1. Simulation of scenario 3.

CONCLUSIONS

In the simulation of the first scenario, the contribution in the maximum power limits of each of the sources is seen, and it is observed that when braking, the storage devices obtain a part of the energy that is produced, while the other is dissipated. In the simulation of scenario two, it is observed that almost all the power required for movement is given by the fuel cell, while the battery and the supercapacitor, although they store energy, do not deliver it to the system when it requires it. For case 3, it is observed that the storage sources deliver the power required for movement. The fuel cell still delivers energy, due to the limited capacity of storage sources, but in a smaller amount than in previous cases. If we do an efficiency analysis based on the amount of power delivered by the battery in cases 2 and 3, we can find that there was an improvement of about 14%.

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