Game Theoretic Approach for electrified auxiliary management in high voltage network of HEV/PHEV

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***Abstract*—Auxiliary electrification becomes a potential solution to reduce the vehicle energy consumption. However, electrified auxiliaries operate mostly in individual way, non-cooperative in regardless of the vehicle state. In this paper, a new control strategy for electrified auxiliary system is proposed in order to improve the coordination among auxiliaries. This new control strategy is not only based on a game theoretic approach but also a model predictive control (MPC). In this approach, each electrified auxiliary is considered as a player participating in an energy consumption game, where players have incentive to cooperate and improve the global vehicle consumption. Simulation results on a plug-in hybrid electric vehicle show that this new control design provides a promising and simple approach to control the electrified auxiliary system.**

***Index Terms*—HEV/PHEV, Energy management, Optimization, Game Theory, Model Predictive Control, Auxiliary Management**

I. Introduction

Auxiliary electrification has become recently an attractive solution to improve the vehicle energy efficiency. Indeed, this electrification allows the auxiliary system to operate independently with respect to the internal combustion engine (ICE). This property results in a lower direct load demand on ICE and a more efficient use of auxiliaries by switching them on or off according to the situation [1]. In addition, while some new technical solutions for fuel reduction such as "Stop and Start" are implemented into the Hybrid/Plug-in Hybrid Electric Vehicle (HEV/PHEV)′s controllers, the electrification of auxiliary system becomes more and more promising [2]. In fact, while the engine has no mechanical load demand at standstill, it could be turned off for fuel saving and activated in driving mode without impact on the auxiliaries′operation. Although the auxiliary electrification is a promising technical solution to reduce fuel consumption in HEV/PHEV, there is not a lot of studies focusing on this topic.

In the energy management context, the importance of the electrical accessories is always neglected while their power consumptions are often supposed to be constant. Moreover, without an accurate analysis of the electrified auxiliary control, the constraints of electric propulsion system such as the charge/discharge power ability of the traction battery, could be violated. The following work mainly focuses on this electrified auxiliary control in HEV/PHEV by proposing a new control concept based on game theory and predictive control. The objective is to implement an approach that allows a collaborative work between electrified auxiliaries in order to avoid high peaks of power on the voltage network, which could damage the battery lifetime and also to cope with the existing hybrid powertrain control.

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Advanced control design of electrified auxiliary system has not been enough investigated in automobile domain. However, many interesting ideas relating to this subject from others fields, such as Demand Side Management (DSM) in Smart Grid [3], [4], Vehicle-to-Grid (V2G)[5], [6] have been developed. In these works, most of the systems try to solve an energy/power management problem. As a result, the control strategies proposed in these works could be theoretically adapted and applied to the electrified auxiliary system of a HEV/PHEV. The mathematical background used in these papers is called game theory [7], [8]. This framework offers tools and techniques that could simply handle the decision-making problem of the multi-agent system.

Regarding to the applications of game theory in DSM and V2G, each electric consumer is considered as a player in an energy consumption game. All energy consumers in this game attempt to schedule and modify their own power consumption by basing on the information about the consumed powers coming from others players, in order to minimize their own bills stemming from energy producers, and/or maximize their comfortability [9], [10], [11], [12]. Such a kind of game is called non-cooperative game that allows each player to maximize its own benefit, without considering the benefit of others. The non-cooperative game leads to an analysis of the existence of Nash equilibrium point and the convergence of the game toward that point [13]. However, while the Nash equilibrium allows the multi-agent systems to facilitate their decision making since no agent benefits from changing unilaterally its strategy at this equilibrium point, the existence of the Nash equilibrium is not always assured. In [14], [15], [16], the authors attempt to ensure the existence of Nash equilibrium by designing the control strategy based on a potential game. One important property of this type of game is that the Nash equilibrium always exists if players play a game with a finite strategy set [17]. This approach has proved its efficiency in several applications and different fields, such as Autonomous Vehicle-Target Assignment problem [18], Sensor

Coverage Problem [19], Wind Power Integration in the Smart Grid [20]. Broadly speaking, the application of game theory on energy management in DSM, V2G has been extensively studied. However, it has not been investigated in the systems having a small time-scale such as the high voltage network of HEV/PHEV. For this reason, the proposed approach for electrified auxiliary control in HEV/PHEV, which is based on game theory is relatively new. In addition, we will elaborate the proposed approach in the Model-based Predictive Control (MPC) framework [21], [22], in order to handle several constraints of the system and increase the auxiliary controller performances [23].

The paper is organized as follows: The electrified auxiliary system and its interface with powertrain are presented in Section II. Section III provides the energy game formulation with Model Predictive Control. Finally, a performance comparison of the proposed control strategy with respect to a standard hysteresis control (ON/OFF control) is given in section IV.

II. Electrified Auxiliary System (EAS)

A. System Description

In HEV/PHEV, the Traction High Voltage Supply network (THVS) of the vehicle, where the Lithium-Ion battery 600VDC and electrical motor are connected to, supplies energy to the Electrified Auxiliary System (EAS). An overview of a parallel powertrain topology and the THVS is given in Fig.1.

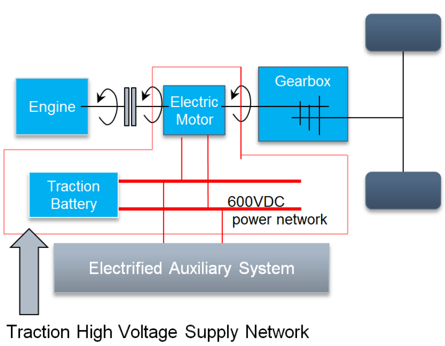

Fig. 1. Powertrain outline of a parallel HEV/PHEV including a Traction High Voltage Supply network (THVS)

The EAS supplied by the THVS network consists of different types of accessories, but it could be generally categorized into two classes: schedulable and deferrable. Indeed, the operation of electrified auxiliaries having a storage component, such as the air conditioning, can be delayed to get the energy efficiency target, as long as the constraints of their storage component are satisfied. In addition, the deferrable electrified auxiliaries in EAS always have an auxiliary battery of a lower voltage network to supply their power demand while the power ability of the THVS network is limited.

In this work, we consider three typical auxiliaries of the EAS in a plug-in hybrid commercial vehicle, which are an electrified air supply system, an electrified refrigerated cargo, and an electrified hydraulic power steering. According to the previous auxiliary classification, the electrified air supply system and the electrified refrigerated cargo are classified as schedulable auxiliaries with the following storage constraints: the pressure in the air tank is maintained in a determined interval for safety reason, and the temperature in the refrigerated cargo is kept at a low value for food-freezing constraint. Regarding to the electrified power steering, this electrified auxiliary could be considered as a deferrable auxiliary because it has an additional 24V DC battery. In some cases, the DC/DC convertor could reduce the power consumption of this auxiliary on the THVS network by limiting the convertor power, and let the 24V battery to participle in auxiliary power supply.

Due to the complexity of the power network where there are two different voltage network levels (THVS and 24VDC low voltage network), the impact analysis of the electrified hydraulic power steering on the vehicle energy efficiency is not straightforward. Consequently, our work focuses more on the electrified refrigerated cargo and electrified air supply system-the schedulable auxiliaries connected to the THVS network.

B. System Modeling

In most of the simulation tools for the HEV/PHEV energy management, the driving cycle just takes into account the vehicle speed profile as a function of the distance or traveling time, and has rarely considered the turn events, which influence directly on the power consumption of the electric hydraulic power steering. Under this limitation and the complexity of the power supply network as previously mentioned, we use only an existing power consumption profile of this auxiliary to describe its impact on the THVS network.

Regarding to the model of the electrified air supply system, the structure of this auxiliary are shown in Fig.2 and fully described in [23]. This auxiliary is composed of an electric

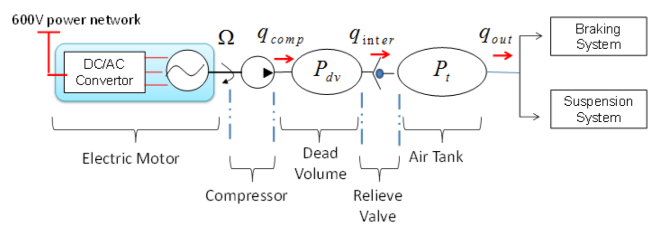

Fig. 2. Electrified air supply system

motor supplied by the THVS network, a screw-compressor driven by the electric motor, a dead volume and finally a tank containing pressurized air dedicated to the operation of others pneumatic components such as the braking system, the suspension system or gear-box transmission. In the context where several auxiliaries are connected to the THVS network, a simple model for each auxiliary is necessary so that the implementation of an auxiliary control could become feasible. As a result, we ignore the dead-volume in the modeling stage. The air pressure inside the tank is the main state variable of the system, and its dynamic at stage $(k+1)$, in discrete-time can be represented by:

$$P(k+1) = P(k) + \frac{\gamma RT}{V}\rho_{air}\Big(q_{in}(k) - q_{out}(k)\Big) \quad (1)$$

where:

$$P_{min} \leq P(k) \leq P_{max}, \quad (2)$$

$$q_{in}(k) = f(P(k), u_{air}(k)), \quad (3)$$

where, P (in bar) is the air pressure in the air tank, T (in K) is the temperature inside the air tank, V (in m^3) is the volume of the tank, γ is the isentropic index of air inside the tank; r, ρ_{air} are the gas constant and the air standard density (in kg/m^3); q_{in}, q_{out} (in NL/min) are respectively the input/output air flow rate of the air tank. $u_{air}(k)$ represents the control variable of the air supply system at stage k. This control variable receives only two values: 1 or 0, which corresponds respectively to an ON/OFF state of the compressor. $f : \Re^+ \times \Re^+ \rightarrow \Re^+$ is a map-based function, which describes the airflow rate at the output of the compressor during the compressing phase. Concerning the auxiliary constraint, the electrified auxiliary operates to compress air in tank, so that the air pressure in tank is kept in an acceptable interval $[P_{min}, P_{max}]$ (in bar) for braking, suspension and others vehicle usages.

The modeling of the presented electrical refrigerated cargo is based mostly on [24], [25]. The structure of this auxiliary is similar to the electrified air supply system, which consists of an electrified actuator (the refrigeration unit), a buffer component (the cargo) that stocks cooled-air and an output load (the heat transfer with the ambient air) (Fig.3). Equation (4) gives the temperature variation in the cargo, as a function of the ambient temperature and power consumption of the refrigeration unit.

$$T(k+1) = (1-\varepsilon)T(k) + \varepsilon\left(T_{amb}(k) - \frac{P_{cooling}(k)}{A}\right), \quad (4)$$

where:

$$T_{min} \leq T(k) \leq T_{max}, \quad (5)$$

$$P_{cooling}(k) = g(T(k), u_{refri}(k)), \quad (6)$$

T(in K) and T_{amb} (in K) are respectively the interior and exterior air temperature, $P_{cooling}$(in W) is the cooling capacity of the refrigeration unit and could be described by (5), in which $g : \Re^+ \times \Re^+ \rightarrow \Re^+$ is a map-based function and $u_{refrig}(k)$ is the control variable of this auxiliary at stage k. This control variable receives only two values: 1 or 0, which corresponds respectively to an ON/OFF state of the refrigeration unit; A is the overall thermal insulation (W/K) of the cargo, ε is the thermal constant of the cargo. In this case-study, we utilize only short driving cycles so that there is no opening door event during a driving cycle. In addition, the refrigeration unit operates to maintain the air temperature within a determined temperature interval $[T_{min}, T_{max}]$.

While the EAS model is implemented into the complete vehicle model, the information that allows an evaluation of the interaction between the EAS and powertrain system is the electric power consumption of each electrified auxiliary. These

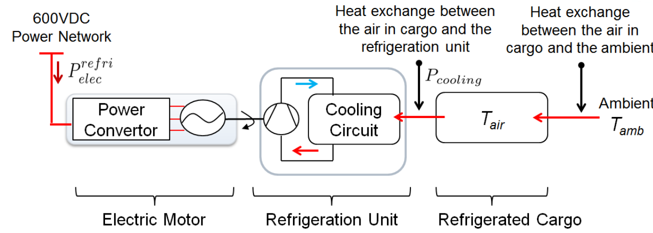

Fig. 3. Electrified refrigerated cargo

power consumptions depend only on the control and the state variables of the EAS. Their expressions are simply described by the following map-based functions:

$$P_{elec}^{air}(k) = f_1(P(k), u_{air}(k)), \quad (7)$$

$$P_{elec}^{refri}(k) = g_1(T(k), u_{refri}(k)), \quad (8)$$

where, $f_1(P(k))$ and $g_1(T(k))$ are map-based functions, which describe respectively the power consumption of electric compressor and electrified refrigeration unit.

The aggregated power consumption profile of three electrified auxiliaries under consideration is shown in the Fig.4. This profile is obtained while launching these auxiliary models in a completed vehicle simulation platform. Each auxiliary in the EAS has different power rates, dynamic behaviors. Regarding to the energy consumption aspect, the simulation shows that in some cases, the energy consumption of the EAS could save 12% of the total vehicle energy consumption. In addition, with a decentralized control, the EAS could create critical-power peaks on the THVS network during the driving cycle without taking into account the ability of the components such as the traction battery, the electric motor and so on. This result confirms again the fact that the energy/power management for electrified auxiliary system is essential.

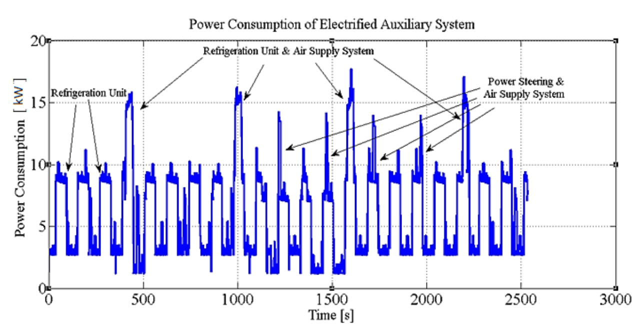

Fig. 4. Power consumption profile of EAS

III. Energy Consumption Game

A. Problem Reformulation

The proposed idea for load shifting problem in [26] shows that it is essential to distinguish firstly the energy producers and energy consumers in HEV/PHEV. With the assumption that the mechanical loads in HEV/PHEV are very small in comparison to the power demand of EAS and vehicle propulsion, we can describe the relation between energy consumers and energy supplier as the Fig.5. The HEV/PHEV has only one energy supplier, which is considered as a combination of the engine, the electric motor and the Lithium-Ion battery. The two energy consumers of the system are the vehicle propulsion and EAS. The power demands of energy consumers depicted in Fig.5 are respectively $P_{demand-propulsion}$ and $P_{demand-aux}$.

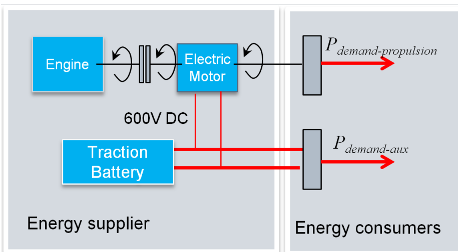

Fig. 5. Supplier-Consumers formulation in HEV/PHEV

In order to have a simple approach, we assume that the energy production cost of the supplier at each stage k is a quadratic function, which depends on the total power provided by the vehicle propulsion, EAS and the State-Of-Charge (SOC) level of the traction battery:

$$\begin{aligned} &J(P_{eaux}, P_{prop}, SOC_{level}) = \\ &= (1-\alpha \times SOC_{level}(k))(P_{eaux}(k)+P_{prop}(k))^2, \end{aligned} \tag{9}$$

and:

$$P_{eaux}(k) = \textstyle\sum_{i=1}^{N} P^i_{eaux}(k), \tag{10}$$

where: N is the number of electrified auxiliaries in the THVS network, $P^i_{eaux}(k)$, $\forall i = 1, ..., N$, is the power consumption of the i^{th} electrified auxiliary connecting to THVS at stage k, and these variables are the control variables of the system on scope; P_{eaux}, P_{prop} are respectively the power demand of EAS and vehicle propulsion, with:

$P_{eaux} \geq 0$:while EAS requires energy from the THVS

$P_{prop} \geq 0$:while the electric motor assists the engine

$P_{prop} \leq 0$:while the electric motor operates as an alternator

and α is a tuning parameter that satisfies: $1/max(SOC_{level}) > \alpha > 0$; SOC_{level} corresponds to traction battery state of charge level (=0:very low,=1:low, =2:normal,=3:high, and =4:very high). The reason why we do not consider the SOC value in this case study is that it is difficult to obtain an accurate estimation of SOC value in the future. Hence, in this case, a coarse prediction on SOC value for the auxiliary scheduling makes more sense than an exact prediction. Applying this proposed cost to the Load Shifting aspect of EAS, the cost function to minimize is calculated on a time prediction horizon of T_p seconds, as the follows: :

$$\begin{aligned} &\min_{P_{eaux}} \sum_{h=k}^{k+T_p} J(P_{eaux}(h)) = \\ &= \min_{P_{eaux}} \sum_{h=k}^{k+T_p} (1-\alpha SOC_{level}(h))(P_{eaux}(h)+P_{prop}(h))^2, \end{aligned} \tag{11}$$

where:

$$T_{min} \leq T(k) \leq T_{max}, \tag{12}$$

$$P_{min} \leq P(k) \leq P_{max}, \tag{13}$$

With this approach, EAS does not have any benefit to withdraw energy from THVS network when the vehicle accelerates, because the consumption during that phase could increase dramatically the cost function J of the energy supplier. Besides, when the vehicle decelerates, the consumption of EAS could reduce the cost J due to its quadratic form, so the electrified auxiliaries are encouraged, with the proposed approach, to get "free energy" regeneration by the electric motor during deceleration phases.

We assume that the power demand of the vehicle propulsion P_{prop}, and the SOC_{level} varying on a considered horizon are exactly anticipated thanks to new technologies such as GPS, GIS, ADAS. With this assumption, equation (11) could be solved by using a centralized algorithm to determine the optimal power flows $P^i_{eaux}(k), \forall k = 1, ..., T_p$and $\forall i = 1, ..., N$ on a prediction horizon. However, the computation burden could be a problem in real-time control, while the number of electrified auxiliaries in EAS increases, and the auxiliary constraints (e.g. air pressure limit, air temperature limit) have to be taken into account. To overcome this problem, Game Theoretic Approach and Model Predictive Control (MPC) are utilized and presented in the following sections.

B. Game Formulation

From (10), the decision-making in power demand of each autonomous auxiliary in EAS depends on how the others schedule their consumption. This fact leads to a game among electrified auxiliaries:

- Players: electrified auxiliaries in a set of N auxiliaries
- Strategies: power demand vector $\underline{P^i_{eaux}}(k) = [P^i_{eaux}(k), P^i_{eaux}(k+1), \ldots, P^i_{eaux}(k+T_p)]$ of the player i to maximize a utility on a prediction horizon $[k, k+T_p]$
- Utilities: $U_i(\underline{P^1_{eaux}}(k), ..., \underline{P^i_{eaux}}(k), ..., \underline{P^N_{eaux}}(k)) = U_i(\underline{P^i_{eaux}}, \underline{\boldsymbol{P}^{-i}_{eaux}})(k)$ for the player $i = 1, 2, ..., N$ at k stage:

$$\begin{aligned} U_i(\underline{P^i_{eaux}}, \underline{\boldsymbol{P}^{-i}_{eaux}})(k) = -\Bigg[&\sum_{h=k}^{k+T_p} J\Big(P^i_{eaux}(h) + \sum_{j\in N/\{i\}} P^j_{eaux}(h)\Big) \\ &- \sum_{h=k}^{k+T_p} J\Big(\sum_{j\in N/\{i\}} P^j_{eaux}(h)\Big)\Bigg] \end{aligned} \tag{14}$$

where $\underline{\boldsymbol{P}^{-i}_{eaux}}(k) = [\underline{P^1_{eaux}}(k), \underline{P^2_{eaux}}(k), \cdots, \underline{P^{i-1}_{eaux}}(k), \underline{P^{i+1}_{eaux}}(k), \cdots, \underline{P^{N-1}_{eaux}}(k), \underline{P^N_{eaux}}(k)]$ denotes the set of power demand vectors on a prediction horizon $[k, k+T_p]$ of players others than the player i^{th}; J is expressed in (9). For the i^{th} player, maximizing this utility U_i at each stage k corresponds to search $\underline{P^i_{eaux}}(k)$ that could minimize the marginal impact cost of the ith auxiliary on the vehicle consumption. In brief, according to the proposed game formulation, this energy game is a finite game on a prediction horizon $[k, k+T_p]$.

Normally, in this kind of game where there are several players and each player has a self-interest, the players' strategies converge to an equilibrium point if this point exists, so called

Nash Equilibrium. The definition of this concept is presented as follows:

Definition III.1. *(Nash equilibrium concept for multi-player game): Consider a finite game with N players. Each player i has a finite action set $\boldsymbol{A}_i$ and a utility function $U_i : \boldsymbol{A} \rightarrow \Re$, where $\boldsymbol{A} = \boldsymbol{A}_1 \times \boldsymbol{A}_2 \times \cdots \times \boldsymbol{A}_N$. An action profile of all players is denoted by $a = (a_1, \cdots, a_N)$, where $a \subset \boldsymbol{A}$, and $\boldsymbol{a}_{-i} = (a_1, a_2, \cdots, a_{i-1}, a_{i+1}, \cdots, a_N)$ denotes a profile of players′ action except for the player i. For all $i = 1, .., N$, an action profile $a^* = (a_1^*, ..., a_{i-1}^*, a_i^*, a_{i+1}^*, ..., a_N^*) = (a_i^*, \boldsymbol{a}_{-i}^*) \subset \boldsymbol{A}$ is called a pure Nash equilibrium if:*

$$U_i(a_i^*, \boldsymbol{a}_{-i}^*) = \max_{a_i \in \boldsymbol{A}_i} U_i(a_i, \boldsymbol{a}_{-i}^*). \tag{15}$$

Property III.2. *With this definition and the game formulation presented previously, the existence of Nash equilibrium of this game is always ensured$^+$.*

<u>**Proof:**</u> (for the statement$^+$)

Definition III.3. *(Potential game): A game $G = (N, a, U)$ is a potential game if there exists a function $\Phi : \boldsymbol{A} \rightarrow \Re$ such that, for all $i = 1, .., N$; $a_i, a_i' \in \boldsymbol{A}_i$, and for all $\boldsymbol{a}_{-i} \in \boldsymbol{A}_{-i}$, where $\boldsymbol{A}_{-i} = \boldsymbol{A}_1 \times ... \times \boldsymbol{A}_{i-1} \times \boldsymbol{A}_{i+1} \times ... \times \boldsymbol{A}_N$, we have:*

$$U_i(a_i, a_{-i}) - U_i(a_i', a_{-i}) \geq 0 \Leftrightarrow \Phi(a_i, a_{-i}) - \Phi(a_i', a_{-i}) \geq 0 \tag{16}$$

We define the potential function $\Phi : \boldsymbol{A} \longrightarrow \Re$ as the following expression:

$$\begin{aligned} \Phi(a)(k) &= \Phi(a_i, a_{-i})(k) = \Phi(\underline{P_{eaux}^i}(k), \underline{\boldsymbol{P}_{eaux}^{-i}}(k)) \\ &= -\sum_{h=k}^{k+T_p} J\Big(\sum_{j=1}^{N} P_{eaux}^j(h)\Big) = -\sum_{h=k}^{k+T_p} J\Big(P_{eaux}^i(h) + \sum_{j \neq i}^{N} P_{eaux}^j(h)\Big), \end{aligned} \tag{17}$$

Then:

$$U_i(a_i, a_{-i}) - U_i(a_i', a_{-i}) = \Phi(a_i, a_{-i}) - \Phi(a_i', a_{-i}),$$

Consequently, (16) is always true, then the proposed energy game is a potential game. Moreover, the potential game has an important following property:

Property III.4. *Every finite potential game has a pure Nash equilibrium.*

Then, the existence of the Nash equilibrium in the proposed game is always assured.■

Furthermore, there are many efficient algorithms for such kind of game that could converge to the Nash Equilibrium, such as: best response, fictitous-play, rational learning, Q-learning and so on [14], [15], [16]. In order to have a simple approach, we propose to utilize the best response strategy for this game. The best-response strategy is described in the Section III.D and its performance analysis is presented in the Section IV.D.

C. Model Predictive Control

Different from the Demand Side Management (DSM), the term ″prediction control″ for energy management in automobile domain has more constraints relating to real-time possibility and prediction accuracy. Indeed, the prediction horizon in DSM is normally chosen 24 hours ahead. Therefore, the computation time to determine the optimal solution of the energy management problem is negligible in comparison to the prediction horizon, whereas the prediction horizon in automobile should be selected just long enough for real-time implementation. Up to now, technologies such as GPS or GIS could provide an anticipation on a short horizon, and have difficulties to take into account the intermittent events on the road like traffic lights, accidents and so on. In order to overcome these limitations, we propose to introduce the previous game for EAS into a model predictive control (MPC) framework [23], in which electrified auxiliaries play a finite game within a receding horizon

The principle of MPC is to calculate a future control sequence that minimizes a cost-function, which reflects the optimization problem subject to several constraints. Then, only the first element of this sequence is applied to the system. This process is repeated after the application of the first element of the control sequence on the system. Therefore, with the previous game formulation, the control variables of the MPC framework are the sequence of activation/deactivation power demand vectors: $\underline{P_{eaux}^i}, \forall i = 1, \cdots, N$ and the optimization problem consists in maximizing the utility function (14) of each player. This optimization problem is solved by using the mesh-adaptive direct search algorithm (MADS) presented in [27], [28].

D. Distributed Algorithm

In accordance with Section II.B and II.C, we suppose that the electrified auxiliaries are able to cooperate to schedule their energy consumption on a receding prediction window. In this section, we provide an algorithm and a control structure for the proposed game. The data flow of the proposed distributed

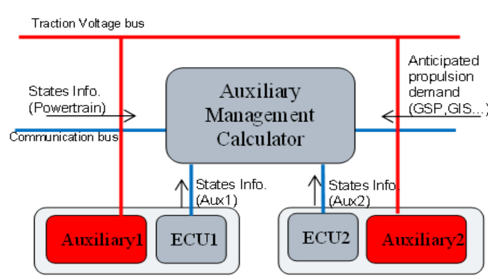

Fig. 6. Data Flow

algorithm is shown in Fig.6. At each stage k, the Electric Calculator Unit (ECU) of each auxiliary in EAS sends information about the auxiliary states to the Auxiliary Management Calculator (AMC), via a communication bus. With the information, provided by drivetrain calculators, auxiliary calculators, and from GPS or GIS, such as SOC_{level}, upcoming propulsion power demand P_{prop}, the AMC determines the best scheduling for electrified auxiliaries within a sliding window.

A distributed algorithm is implemented to solve the optimization as a game with virtual players corresponding to electrified auxiliaries under consideration. The diagram Fig.7 highlights the different steps of the algorithm: Note that at

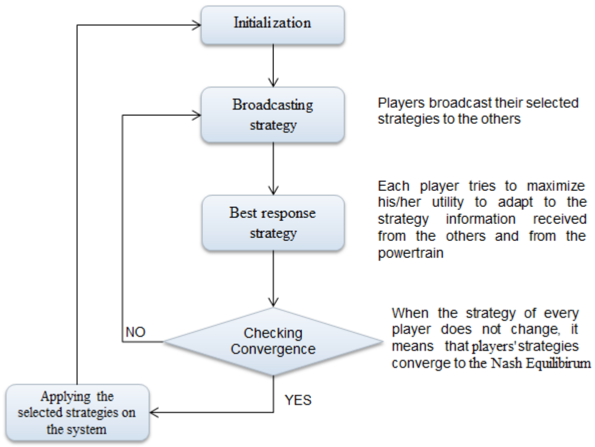

Fig. 7. Distributed algorithm

each stage k, when the strategies of players converge to Nash Equilibrium, AMC will select these strategies and apply them to the EAS. At stage $(k+1)$, these strategies are recalculated from the Initialization step for a new prediction horizon $[(k+1),(k+1+Tp)]$.

IV. Simulation

In this section, we present the simulation results of this new approach, and point out its advantages. Three aspects are investigated in order to assess the relevance of this new approach: energy cost consumption, peak-to-average ratio and algorithm convergence. The simulation platform selected for

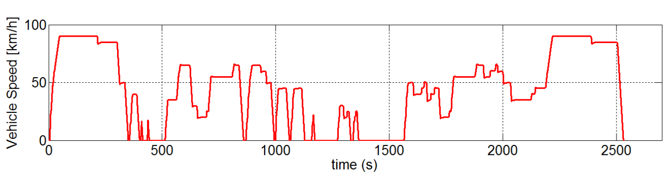

Fig. 8. Driving cycle (internal reference of Volvo)

the simulation is based on a forward-facing model, in which there is a driver model. The vehicle model is a parallel PHEV having 242hp engine and a Lithium-Ion battery with a total capacity of 24kWh. The driving cycle is depicted in Fig.8. The initial conditions for the simulation are:

- Air temperature inside the cargo: -25 (^{o}C)
- Pressure inside the air tank: 10 (bar)
- State-of-Charge (SOC) of the traction battery: 55%
- Vehicle is at standstill

The new control strategy is tested with three different prediction horizons: T_p= 30s, 60s, and 90s. Some simulation results are shown in the following figure:

We find that the compressor compresses air into the tank each time the vehicle is in deceleration phase. Similar to the air supply system, the air temperature of the refrigerated

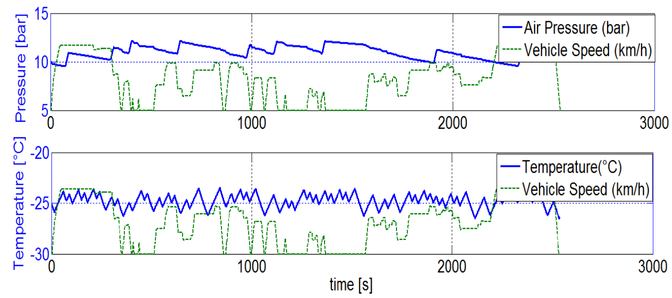

Fig. 9. Air Pressure/Temperature in Air Supply system and Refrigerated Cargo, with Tp=90s

cargo is cooled down while there is a regeneration braking. This load shifting aspect could be clearly pointed out in these simulations (Fig.9) (see also Fig.11). In Fig.10, with the upcoming information on acceleration event, where the utility of the refrigerated cargo decreases drastically if it is activated, the AMC decides to cool down the air in cargo before that event so that the refrigeration unit does not have to cool air during that phase.

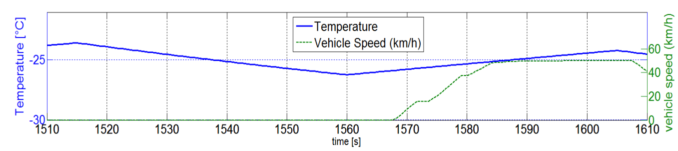

Fig. 10. Temperature inside the refrigeration cargo while the prediction is available

As expected, the algorithm presented in the previous sections allows the two electrified auxiliaries to operate cooperatively in order to minimize the energy consumption cost. Indeed, as shown in Fig.11, the air supply system and the refrigerated cargo are activated at the same time, when there is a braking (e.g. at t=300s or t= 400s). In contrast, they are not activated at the same time to avoid high peak consumptions on the THVS (e.g. at t=80s).

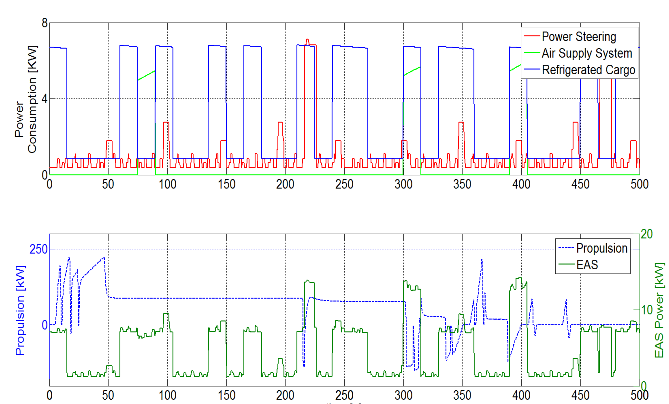

Fig. 11. Cooperation between the electrified air supply system and electrified refrigerated cargo

A. Energy consumption cost

One important assumption for this analysis is that at the end of the driving cycle, the vehicle will be plugged on the electric grid. This assumption seems obvious for any PHEV so that its traction battery is charged while the travel is finished, but it is highly important to compare the effective- cost of different control strategies. In our study, there are several energy buffers in the vehicle architecture. Another assumption is that all energy buffers in EAS such as the refrigerated cargo, the air tank can be charged via the THVS network, while plugging the vehicle on the electric grid.

Based on these assumptions and [29], we propose a method to calculate the effective-cost for PHEV having plural of energy buffers. The total energy consumption cost is described as the following formulas:

$$Cost = p_{diesel}V_{cons} + [p_{elec}\eta_{charger}(\Delta E_{bat} + \sum_i \Delta E_{buffer\_i})], \tag{18}$$

where, p_{diesel} (in euros/L) and p_{elec} (in euros/kWh) are the prices of diesel and electricity respectively; V_{cons} (in liter) is the volume of fuel consumption on the driving cycle; $\eta_{charger}$ is the efficiency coefficient of the THVS charger; ΔE_{bat} (in kWh) is the electrical energy needed to charge the battery from SOC_{end} to $SOC_{initial}$; $\Delta E_{buffer-i}$ (in kWh) is the necessary electrical energy for charging the energy buffer of the i^{th} auxiliary from the end state value to a target-value. The first term of (18) is equivalent to the fuel cost spent to finish the driving cycle. The second term is the necessary electric cost to charge the energy buffers in the vehicle while plugging on the electric grid.

TABLE I
COMPARISON OF COST OF ENERGY CONSUMPTION

	Fuel Cons(L/100km)	Final SOC(%)	Final Press. (bar)	Final Temp.(^{o}C)	Cost Reduction(%)
Hysteresis	25.4156	38.03	9.808	-24.38	0
Tp=30s	25.4007	37.82	11.52	-26.01	0.08
Tp=60s	25.3873	37.83	11.68	-25.96	0.14
Tp=90	25.1962	37.69	11.64	-26.36	0.89

The target-value for the temperature inside the cargo and the pressure in the air tank are -26.5[^{o}C] and 12.5 [bar] respectively. Tab.1 shows a comparison of potential benefits given by this method with different values for the horizon T_p. It is noteworthy that the longer prediction horizon is, the better gain is obtained. Tab.1 also provides the results obtained with hysteresis control (ON/OFF control) in order to give a referential cost.

B. Minimum Peak-to-Average Ratio (PAR)

In a driving cycle, there are operating conditions while the traction battery is highly discharged for propelling the vehicle. Consequently, if EAS requires power from THVS at these phases, it could cause a voltage drop on the traction battery. This fact could imply a degradation of electrical components in THVS. In some cases, it could also influence on the drivability of the vehicle. In order to analyze this problem, we consider the minimum Peak-to-Average Ratio (PAR) on the discharging phase of the battery, which is defined as follows:

$$PAR = \frac{T_{cycle}\max_k(P_{discharge}(k))}{\sum_k P_{discharge}(k)}, \tag{19}$$

where, $P_{discharge}$ (in kW) is the power consumption of the battery while being in discharging mode; T_{cycle} is the total duration of the discharging phase of the battery. Fig.12 shows the PAR corresponding of four cases: hysteresis control (ON/OFF control) and the new approach with T_p=30s, 60s, 90s respectively.

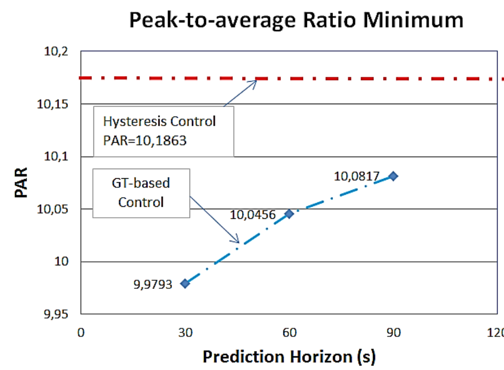

Fig. 12. Minimum Peak-to-average Ratio

According to this result, we could conclude that the proposed approach in this paper allows a PAR reduction on the battery discharge compared to the basic hysteresis control.

C. Convergence Analysis

As shown in Fig.13, the algorithm presented in Section IV.D can find the equilibrium of the energy consumption game in most of the cases. The number of iteration needed to converge to the equilibrium is small (maximum three iterations) while the algorithm converges.

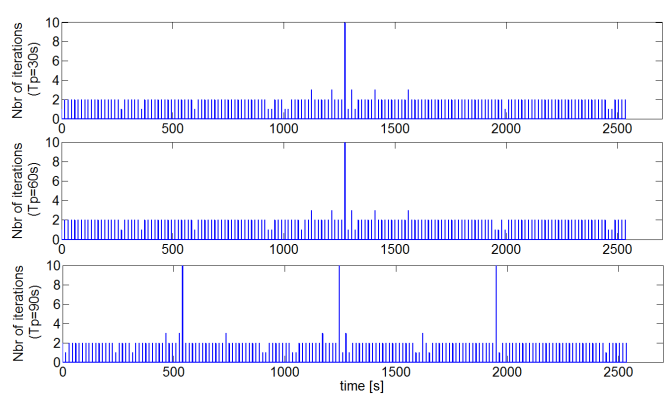

Fig. 13. Number of iterations necessary to converge to Nash equilibrium in three cases: Tp=90s, Tp=60s and Tp=30s

However, there are always some cases in which the algorithm does not converge and has to be forced to stop. This result shows that the best response algorithm may become inefficient in some cases. As a consequence, other algorithms such as fictitious-play, rational learning, Q-learning and so on, are essential to improve the convergence aspect of the energy consumption game.

V. CONCLUSION

In this paper, we present a new control strategy that is based on game theory for the electrified auxiliary system in Plug-in Hybrid Electric Vehicle (PHEV). This technique is combined with a Model-based Prediction Control in order to improve the cooperation among electrified auxiliaries of the system. The simulation results show that the energy cost reduction could attain to 0.89%, and the peak-to average ratio of the THVS network could also be improved with the new control strategy.

Future works concern the improvement of the distributed algorithm in order to assure the convergence to Nash equilibrium in every decision-making of the EAS. In addition, the introduction of the DC/DC convertor into the game will be considered. Furthermore, the energy production cost of the powertrain will need to be investigated more thoroughly.

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