

Energy Management in multi-consumers multi-sources System : A Practical Framework ^{*}

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Abstract: The paper develops a methodology to design a practical Multi-sources and Multi-consumers energy management systems (EMS), applicable in particular to transport systems. A global EMS optimization problem is formulated underlining generic criterion and constraints. Remarking that a modularity property is essential to add easily (i.e. without redesigning the whole problem) new energy consumers (or sources), a new EMS structure is presented, splitting the problem into two independent sub-problems. In compensation of sub-optimality, the computing burden is lightened and robustness to energy shortage enhanced. The framework is introduced through the EMS design of a hybrid vehicle transporting conditioned merchandises.

Keywords: Energy management systems; Methodology; Hybrid vehicles; Predictive control

1. INTRODUCTION

The development of Hybrid Electric Vehicle (HEV) and the new generation of Plug-in HEV (PHEV) motivate the studies, both by car manufacturers and by researchers, about Energy or Power Management Systems (EMS, PMS), driving in real-time the energy flows from several sources (Engine, Batteries, Fuel Cell) to potentially several consumers (propulsion, auxiliaries such as the heating system) embedded in vehicles. Two main categories of EMS can be distinguished in the literature: ruled-based and optimization algorithms.

The first category makes use of tools such as fuzzy logic (Lee et al. [2000]) or deterministic approaches (state machine) such as the Charge Depletion - Charge Sustaining algorithm (see Banvait et al. [2009], Wirasingha and Emadi [2011]). These EMS are quite easy to implement, but lead to sub-optimal fuel consumption. The second drives the sources to their optimal point, taking advantages of knowledge about the environment (Luu et al. [2010]). Implemented in real-time, optimization-based EMS have to cope with the prediction; many solutions are based on Deterministic or Stochastic Model-Predictive Control (Ripaccioli et al. [2010]), (Delprat [2002]). Unlike ruled-based EMS, these strategies can be more complex to implement.

To the authors knowledge, most of these results have to deal with several sources (Engine, batteries, fuel cell, regenerative braking) but only one consumer (propulsion), except interesting results proposed by Kachroudi et al. [2012] were two energy consumers (propulsion and

heating system) but one source (Full Electric Vehicle) are considered.

Our objective here is to provide a methodology to design an EMS that:

- (1) deals with real multi-sources / multi-charges problems,
- (2) has an universal and modular implementation structure,
- (3) is weakly CPU-time consuming

This paper proposes a generic EMS structure based on a *power management* unit (called *EMS-PM*) in interaction with decentralized controllers (*EMS-client*) associated to each energy consuming channel (named *client* in this paper) and a general supervisor (*EMS-GSI*). The EMS-PM has two distinct objectives: 1/ to distribute the power flow between the different power demands of the clients thanks to a rule-based strategy, 2/ to drive the different sources thanks to a devoted optimization process. These subproblems are addressed separately and optimized at different sampled time. Local power controllers associated to each client carry out the power management of the associated load, and communicate with the main unit through a given protocol. Controllers are designed once, off-line, and the rule-based strategy implemented to distribute the power flow between them is weakly CPU-time consuming. Notice that several kinds of power energy could be considered and mixed (mechanical, electrical, ...).

The paper is organized as follows; in section 2 the global optimization problem of energy management is proposed, and through its decomposition the architecture of the EMS is introduced. The structured EMS, its constitutive elements as well as the optimization subproblems are de-

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scribed in section 3. The framework is then applied in section 4 to the case study of an hybrid delivery truck with a refrigerating compartment. Finally, some conclusions and perspectives are discussed in section 5.

2. OPTIMIZING ENERGY MANAGEMENT

Let's consider a global system made up of n^c systems requesting energy (clients) and n^s systems providing energy (sources and/or storages). The following assumption is made : **(A.1)** : All sources share the same energy bus. A central optimization problem considered (sometimes implicitly) in the literature dealing with **power management**, consists to :

Find an optimal energy distribution that satisfies the system missions while minimizing the overall energy cost. The mission of each subsystem may be achieved with different levels of satisfaction. The system is governed either by dynamic and discrete event equations and constraints.

In most cases, it may be formalized by **Problem P_{glob}** where the decision variables are:

- the controlled sources power signals
- the consumers power signals; this signals can be regulated (in particular by changing *ad hoc* the control command parameters or references; cf. Bond Graph (e.g. (Borutzky [2010]))

Problem P_{glob}

$$\arg \min_{\substack{P_1^c, \dots, P_{n^c}^c \\ P_1^s, \dots, P_{n^s}^s}} = \sum_{i=1}^{n^c} \bar{S}_i(P_i^c) + \sum_{j=1}^{n^s} (Ec_j^s(P_j^s) + Ac_j^s(P_j^s))$$

Subject to :

$$\begin{aligned} & \text{the system dynamics} \\ & \text{Limited sources capacity (e.g. SOC)} \\ & \sum_{i=1}^{n^c} P_i^c = \sum_{j=1}^{n^s} P_j^s \text{ implies by (A.1)} \\ & \forall j \in \llbracket 1, \dots, n^s \rrbracket, P_j^s \in [P_j^{min}, P_j^{max}] \end{aligned}$$

The criterion is composed of two parts. One is associated to the clients and their *dissatisfaction level* $\bar{S}_i(P_i^c)$ with P_i^c the power profile applied to consumer i . The other, represents the sources and regroups the energy cost, $Ec_j^s(P_j^s)$, and the additional costs (e.g. comfort, gas emission,...), $Ac_j^s(P_j^s)$, when the power P_j^s is drained from the source j . In real time, solving the control problem satisfying both objectives could lead to a heavy computation burden.

According to the authors, defining a single (global) optimal problem is not convenient to deal with most practical problems. It doesn't match the modular property that makes possible to add a new energy elements (source or consumer), without redefining and solving again the whole problem and reprogramming the whole EMS.

Moreover, during their mission, most of the systems are considered autonomous. This means that they have to deal with limited energy resources. Miss-sizing or strong disturbance may involve the system to run out of energy before the mission ends. In order to prevent the mission to

fail, energy needs can be decreased by reducing consumers performance. Therefore, the problem is not anymore only focused on the dynamics optimization. In the context of multiple energy consumers, the EMS has to select which one(s) will have to operate in a degraded mode.

Motivated by these remarks, a structured EMS is proposed here and depicted in Figure 1. The classic EMS is dispatched according to the elements energy properties (consuming or supplying). Each part corresponds to a sub-problem of **problem P_{glob}** . The framework matches industrial representation based on *Systemic Modeling* (Eriksson [1997]) and deploys, in particular, in (Sherpa Engineering). Moreover, the dynamics regulation problem could be synthesized offline while the energy supply problem must be solved in real-time by the entity called *Power Manager (PM)*.

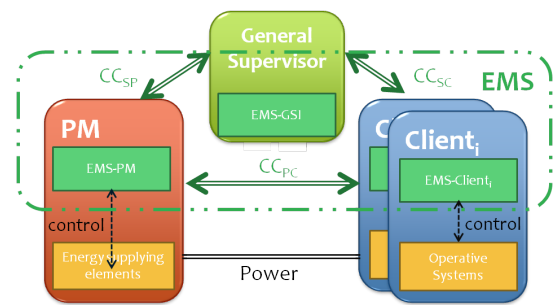


Fig. 1. EMS Decomposition

3. A PRACTICAL POWER MANAGEMENT FRAMEWORK

The proposed framework relies on a specific EMS partitioning based on three entities : a *Power Manager (PM)*, a *general supervisor* and *clients* (see Figure 1). The general supervisor aims to communicate mission events and *GSI-strategies* (defined in section 3.2). Due to its close similarity with user interface, this elements is named *EMS-General Supervisor Interface (EMS-GSI)*. Clients and PM will be explained in the next parts. Communication Channels (CC) are illustrated by double arrows while double lines represent the multi-energy link.

3.1 The clients

A client regroups organs and local control which are aiming to a specific purpose (mission). For example, a car powertrain has to respond to a mobility mission. These elements and their control could be gathered under the label *mobility client*. Figure 2 gives a macroscopic view of what we called a *client*, through its inputs and outputs. It is made up of the following elements :

- the *EMS-client* : it implements different strategies to achieve the assigned *mission* , for different amount of energy. The possible strategies are defined by considering a set of admissible configurations.
- the *configurations set* ; each configuration matches a specific power request over time, all admissible although corresponding to different levels of sub-optimality; the request is assumed to be generated

in real-time, although prepared off-line; using various controllers (e.g. LQ controllers with distinct weights), or to select different references.

- the operative systems (with their local closed-loop)

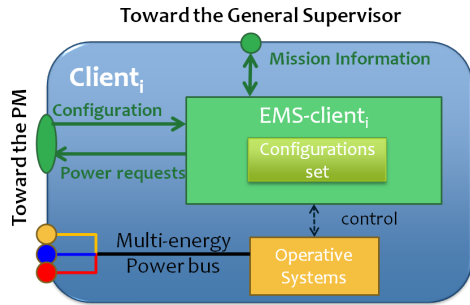


Fig. 2. The Client's system architecture

Requests are generated at the sample time ΔT_{PM} which differs from the local regulator sample time. Thanks to this property, profiles can be updated at low sample time while the operative systems are driven at a quicker frequency.

Example 1 Let's consider a room receiving energy from photo-voltaic panels and a set of batteries. The room and heaters inside will be called comfort client. One reference signal defines one configuration. A set of configurations may be defined through the use of different temperature references and/or controllers. Let's add the light control to our problem. All artificial light sources and their local controllers are gathered into the luminous comfort client. Identically, the configurations set can be composed of different luminous intensity levels.

3.2 The Power Manager (PM)

In the PM (cf. Figure 3), two tasks are realized : 1) arbitrate energy requests between clients, 2) manage the energy supplying channels. For that reason, the power management will be separated in two problems consisting on one side in *energy supplying optimization* and on the other side in *inter-client energy optimization*.

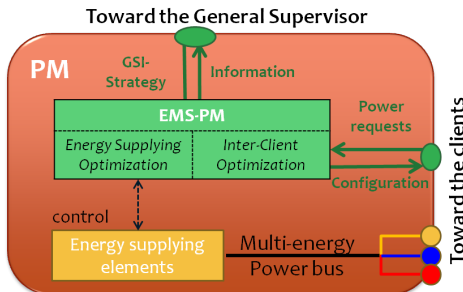


Fig. 3. The PM's system architecture

The energy supplying elements box stands for the symbolizes systems (and their local controllers) which are acting as energy sources.

a) Inter-client Optimization

Consider a problem with n^c clients. Each client i is assumed to propose N_i^g configurations (admissible power demand profiles sampled at ΔT_{PM}) to the PM. For every client i , power profiles P_i^j are sorting by their energy levels (i.e. E_i^j) in descending order. The configuration corresponding to the highest cost E_i^1 is called *nominal power profile*. Others profiles are expressed as deviation signals from the nominal :

$$\delta P_i^j = P_i^1 - P_i^j \quad (1)$$

The following claim is assumed.

(A.2) : For every client i , the dissatisfaction level is directly linked to the deviation power signal :

$$\bar{S}_i(P_i^j) = f_i(\delta P_i^j) \quad (2)$$

Proposition 1. The inter-client optimization sub-problem P_{ic} can be simplified by defining function f_i as :

$$f_i(\delta P_i^j) = \delta E_i^j \quad (3)$$

Where δE_i^j is the *energy deviation value* for client i defined by (4) with t_f the estimated final time of the mission. These values are grouped in the set \mathcal{C}_i .

$$\delta E_i^j = \int_t^{t_f} \delta P_i^j(\tau) d\tau \quad (4)$$

This proposition is a suggestion from the author allowing to write the criterion with positive signals consistent with energy variables. The sub-problem, extracted from P_{glob} and associated to the clients can be finally formulated as :

Problem P_{ic}

$$\arg \min_{\delta E_1 \in \mathcal{C}_1, \dots, \delta E_{n^c} \in \mathcal{C}_{n^c}} \sum_{i=1}^{n^c} \alpha_i \delta E_i$$

subject to :

$$\begin{aligned} \sum_{i=1}^{n^c} E_i^c &\in E_{tot}^s \\ \sum_{i=1}^{n^c} P_i^c &= P_{tot}^c \in [P_{tot}^{min}, P_{tot}^{max}] \end{aligned}$$

Where α_i describes priorities between clients and will be tagged as a *GSI-strategy* implied by the *EMS-GSI*. For example, a car strategy could be *comfort* or *performance* whether the highest importance is given to the passenger compartment or the mobility.

E_{tot}^s , P_{tot}^{max} and P_{tot}^{min} are respectively the amount of energy, the maximum power and the minimum power available from the sources channels (i.e. without any distinction between the different sources).

b) Energy supplying optimization

In this paper, a source refers to any element, including its local controller, which has been designed in the purpose of providing or storing energy. They can be distinguished according to their capacity, controllability (ability to be controlled) and reversibility. Figure 4 depicts the sources repartition. Commonly, limited reversible sources are named *storage element*. Their energy capacity is denominated *State of Charge (SOC)*.

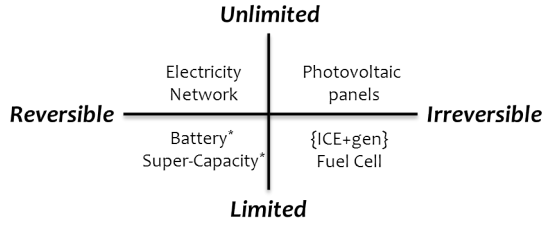


Fig. 4. Example of sources repartition; the * indicates uncontrollable sources

As soon as there is more than one source, the energy optimization problem is over-actuated. Hence, the energy supplying problem is double. On one hand, the EMS-PM must satisfy the resources allocation problem between the redundant actuators. And on the other hand, it must guaranty power demands from clients.

The *energy supplying problem* is equivalent to control the sources in a way that the total energy cost is minimized and all the sources constraints are satisfied :

Problem P_{es}

$$\arg \min_{P_1^s, \dots, P_{n^s}^s} \left(\sum_{j=1}^{n^s} (Ec_j^s(P_j^s) + Ac_j^s(P_j^s)) \right)$$

subject to :

$$\sum_{j=1}^{n^s} P_j^s = P_{tot}^c \text{ implies by (A.1)}$$

$$\forall j \in \llbracket 1, \dots, n^s \rrbracket, P_j^s \in [P_j^{min}; P_j^{max}]$$

Sources dynamics
Limited sources capacity (e.g. SOC_s)

Where $Ec_j^s(P_j^s)$ and $Ac_j^s(P_j^s)$ correspond respectively to the energy cost and the additional cost when the power P_j^s is drained from the source j .

Remark : The *inter-client optimization* as a part of the EMS-PM, provides the estimated total power request P_{tot}^c over the future time-horizon τ_p . Therefore, the P_{es} problem can be efficiently solved thanks to predictive or preview control strategy as MPC (Wang [2009]) or H₂-preview results (Saleh et al. [2010]).

4. ILLUSTRATION

The previous framework has been applied in order to design the EMS for a hybrid refrigerating truck. The selected powertrain architecture is serial and the energy supplying chain is composed of an Internal Combustion Engine (ICE) coupled with a generator (notated shortly ICE-G) and a battery (see Figure 4). The propulsion is achieved through an electrical machine (MEL). The thermally insulated compartment is cooled using a heat pump (HP). The simplify powerline is represented by Figure 5 and the algebraic relation :

$$P_{bat}^s = P_{mob}^c + P_{ref}^c - P_{gen}^s \quad (5)$$

The mission considered is a pick-up and delivery problem. It could be literally expressed by :

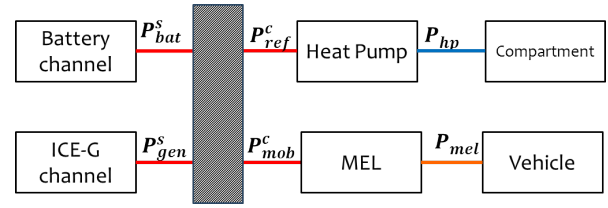


Fig. 5. Simplified energy Network

Supplied by a certain amount of energy, the vehicle must ride a known itinerary. Along its journey, the vehicle will stop to delivery. The refrigerated goods shall not overpass a specific temperature. The mission is achieved if the vehicle reaches its destination while the goods temperature has been maintained all over the journey.

Let's design an EMS for this hybrid refrigerating truck by using the proposed framework. In subsection 4.1 all the offline works is described; definition of the two clients (mobility and refrigerating compartment), their models and their configuration sets (profiles). Models of the two sources are also provided. The design of the real-time optimization solvers constituting the EMS-PM is addressed in subsection 4.2. The driver is assumed to respect as best as he can the proposed action.

4.1 EMS-clients settings

a) *The Mobility Client:* This client is associated to the subsystem Vehicle and the actuator MEL (cf. Figure 5). The vehicle model relies on the first principle of the dynamic. Only the longitudinal dynamic is modeled, as follows

$$M \frac{dv}{dt} = F_{tract} - \lambda v^2 \quad (6)$$

With λ the aerodynamic friction coefficient, v the vehicle speed and M the total mass (i.e. vehicle and load included). See Table 3 for parameters values.

The MEL is limited to 75kW during the driving phase. During the braking phase, 45% of the energy can be recovered by the regenerative flow up to 55kW. Dynamics are neglected leading to characterize the model of the system by the single gain K_{mel} .

$$P_{mob}^c = K_{mel} F_{tract} v \quad (7)$$

P_{mob}^c stands for the mobility power request.

To simplify the illustrative example, the vehicle is considered to be automatically driven (neither a driver model nor an eco-driving interface are necessary). The longitudinal speed is so regulated according to the nominal speed profile depicted in Figure 6, taking also into account the traffic slow down. The nominal mission profile was built on one side from the New European Driving Cycle (NEDC) speed profile, and on the other side, from the break time occurring to load and unload the merchandise.

Since break-times are important in our problem, indexing the reference signal over the time variable t is not relevant. Indeed, the reference has to be robust to traffic variations

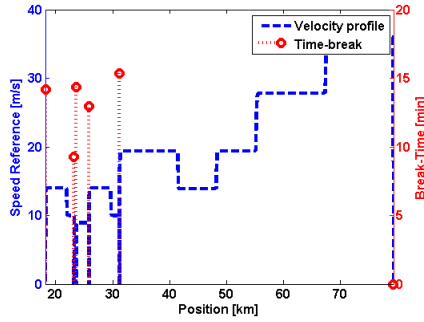


Fig. 6. NEDC speed profile and break-time

and delays.

Hence, the position variable x is used instead of the time.

Finally, notice that the NEDC speed profile is taken into consideration only from 17.5km , to focus on the final and the most interesting part of the mission.

The client is set to generate two different power profiles according to configurations in table 1. As it has been introduced in section 3.2, the energy deviation values are grouped in the set \mathcal{C}_{mob} . The aggressive and smooth control of the vehicle are obtained thanks to two PI controllers, respectively tunes as $(P=250, I=0.5)$, and $(P=100, I=0.2)$.

Table 1. The Mobility Configurations

Configuration	Description	maximum power
P_{mob}^1	Aggressive control and high power limit	$P_{mel_{max}} = 75\text{kW}$
P_{mob}^2	Smooth control and low power limit	$P_{mel_{max}} = 55\text{kW}$

The Figure 7 is an example of the two configurations communicated to the EMS-PM at the position $x_i = 1750\text{m}$. With P_{mob}^2 , the truck will run with a slower speed, allowing to save energy.

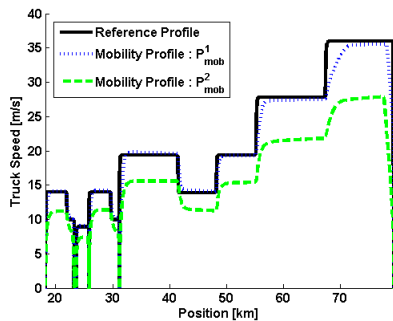


Fig. 7. Mobility profiles P_{mob}^1 and P_{mob}^2 at x_i

b) The Refrigerating Compartment: The physical model (8) is inspired by an example in (Maciejowski [1989]). It represents the heat energy transfer in a room containing a heat pump. The outdoor temperature is considered as a

constant disturbance. Heat accumulation in the walls are neglected as well as heat pump dynamics.

$$\frac{dT}{dt}(t) = K_{closed}(T(t) - T_{ext}) + \frac{1}{c_v}P_{hp} \quad (8)$$

With P_{hp} the heat pump power, c_v the room heat capacity. $K_{closed}(T(t) - T_{ext})$ stands for the heat exchange through the wall. When the vehicle stops, the doors are briefly opened. The additional lose is taking into account by switching K_{closed} to K_{open} as $K_{open} \gg K_{closed}$ (see Table 3).

The refrigerating power demand is noted P_{ref}^c and equals:

$$P_{ref}^c = K_{hp}P_{hp} \quad (9)$$

The heat pump power is adjusted to maintain a reference merchandise temperature T_c , thanks to a simple Proportional controller ($P=200$). This one could be modified according to the Table 2. The energy deviation set associated to this client is \mathcal{C}_{ref} .

Table 2. The Refrigerating Compartment Configurations

Configuration	Description	Reference
P_{ref}^1	Recommended temperature	$T_c = 4^\circ\text{C}$
P_{ref}^2	Maximum allowed temperature	$T_c = 6^\circ\text{C}$

4.2 EMS-PM settings

a) Sources Models: The battery is characterized by its state of charge Soc . This value is continuously estimated by formula (10), with Q_n the nominal capacity, V_{bat} the nominal voltage and P_{bat}^s the outgoing power (see Table 3).

$$Soc(t) = \frac{1}{Q_n V_{bat}} \int_0^t (P_{bat}^s) dt \quad (10)$$

$P_{bat}^s < 0$ means the battery is depleting.

The ICE-G is simply modeled by an efficiency cartography, leading to write :

$$FC(t) = \eta_{gen}(P_{gen}^s(t)) \cdot P_{gen}^s(t) \quad (11)$$

Where P_{gen}^s and η_{gen} are respectively the power supplied by the ICE-G and the associated efficiency.

The fuel consumption $FC(t)$ is expressed in [g/s].

b) Inter-client Optimization: In this illustration, only one GSI-strategy is applied (cf. Figure 1 and section 3.2). The refrigerating client is prioritized over the mobility.

Problem P_{ic}

$$\arg \min_{\substack{\delta E_{mob} \in \mathcal{C}_{mob} \\ \delta E_{ref} \in \mathcal{C}_{ref}}} (\alpha \delta E_{mob} + \beta \delta E_{con})$$

subject to :

$$\begin{aligned} &\text{the GSI-strategy : } (\alpha, \beta) = \{1, 10\} \\ &E_{mob}^c + E_{ref}^c < E_{tot}^s \end{aligned}$$

The amount of energy remaining at instant t in the limited source is :

$$E_{tot}^s = Soc(t) * Q_n * V_{bat} + FC(t) * PCI * \hat{\eta}_{gen} \quad (12)$$

$FC(t)$ and $Soc(t)$ are signals provided by sources (cf. next section). PCI is the Lower Heating Value.

c) *Energy Supplying Optimization:* The P_{es} problem is set as :

Problem P_{es}

$$\arg \min_{P_{gen}^s, P_{bat}^s} (Ec_{gen}^s(P_{gen}^s) + Ec_{bat}^s(P_{bat}^s))$$

subject to :

$$\begin{aligned} & (5) \text{ (due to (A1))} \\ & (10) \text{ and (11)} \\ & Soc(t) \in [0.2; 0.8] \\ & FC(t) < FT_i \end{aligned}$$

$FC(t)$ and $Soc(t)$ describe the fuel consumed by the ICE-G (11) and the battery state of charge (10) at instant t . FT_i is the initial fuel volume in the tank. Energy costs are:

$$Ec_{gen} = P_{gen} \quad Ec_{bat} = Soc(t) - Soc_{ref}$$

The estimated future ICE efficiency $\hat{\eta}_{gen}$ is computed using the cartography and P_{tot}^c , the total amount of power requested by clients.

4.3 Results

The hybrid refrigerating truck is simulated using parameters in table 3. Results focus on the last mission event (i.e. between the position $x_i = 1750m$ to $x_f = 8.10^4m$). At the position x_i , the battery state of charge is initiated at 80% and the reference state of charge $Soc_{ref} = 70\%$. The fuel tank is filled with 10 litres. The PM and the clients run at the sample time $\Delta T_{PM} = 200s$.

Table 3. Hybrid refrigerating truck simulation parameters

Parameters	Description	Value
M	total weight	3432 [kg]
λ	aerodynamic friction coefficient	0.603
K_{mel}	Gain of the MEL model	0.01
K_{closed}	Gain of the closed door model	2
K_{open}	Gain of the open door model	5
c_v	room heat capacity	0.0017
K_{hp}	Gain of the heat pump model	0.1
Q_n	the nominal capacity	302400 [A.s]
V_{bat}	the nominal voltage	220 [V]
PCI	Lower Heating Value	44.8

The main results are pointed out in the Figure 8 . At the distance $x_{s1} = 23km$, the EMS-PM causes the mobility client to switch from the highest energy cost configuration P_{mob}^1 to the lower one P_{mob}^2 at $x_{s2} = 31km$.

In this configuration, the client saves energy and is able to switch back to the configuration P_{mob}^2 . In the mean time, the refrigerating client is maintained to its highest configuration P_{ref}^1 , allowing to guaranty its maximum satisfaction. This results were expecting due to the GSI-strategy chosen.

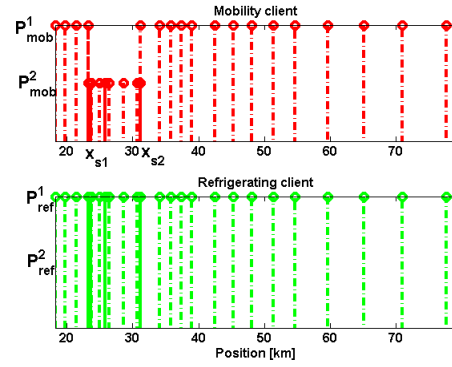


Fig. 8. Configurations Switching

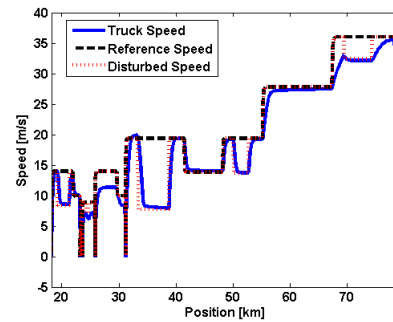


Fig. 9. Mobility Client Results

Figures 9 and 10 permit to verify that the both objectives (i.e. to reach the final destination and to maintain the temperature around a reference) are achieved.

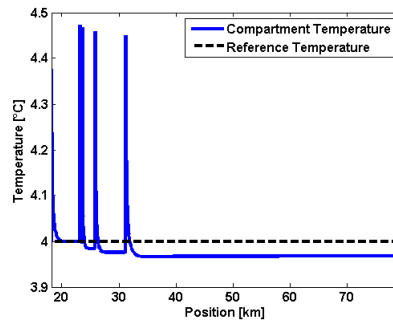


Fig. 10. Refrigerating Client Results

In Figure 10 the several peaks match with the break events when the doors of the fridge compartment are opened. The steady state error at the end could be improved thanks to a more evolved temperature controller.

The different energy consumed by the sources ($Soc(t)$ and $FC(t)$) are displayed in the Figure 11. Sources end the cycle with an energy stock nearly null but still positive (thanks to the configuration switching). The reference state of charge (i.e. 70%) can not be hold at the end due to the high power requests (cf. Fig. 12).

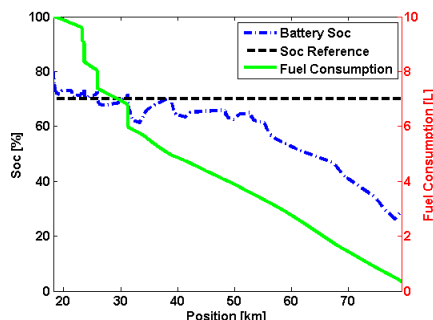


Fig. 11. Energy Consumption : Soc and FC

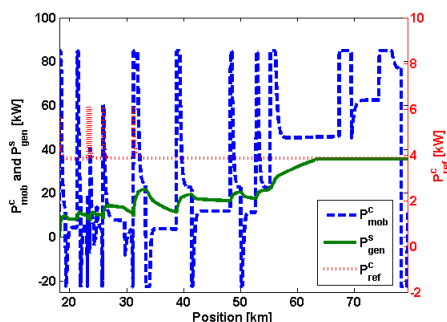


Fig. 12. ICE and Clients power comparison

5. CONCLUSION

The paper introduced a methodology, to design practical Multi-sources and Multi-consumers energy management systems (EMS), applicable in particular to transport systems. After having proposed a global optimization problem to encapsulate the general EMS synthesis problem, the paper presented a general framework for practical design, satisfying the modularity principle. The notion of clients and power sources have been defined, and the associated notions and systems: missions, admissible power profiles sorted and regrouped in a configurations set. The modularity principle allows an independent design of the client local controllers and the EMS, making possible to change or add a new client, without having to redesign the whole system.

The global PMS optimization problem was then reconsidered and split into two sub-problems : the inter-client optimization problem and the energy supplying ones. The first one involves what is called the client dissatisfaction index, while the second is the consumed energy cost. Indeed, the degrees of freedom are twofold : one is to manage at best the energy sources so as to minimize the global energy cost, and the second is, when necessary, to limit the energy attributed to some clients. Both problems were rigorously formalized, leading to a tractable implementation. This was illustrated through the EMS design of an hybrid vehicle transporting conditioned merchandises.

All advantages from the proposed framework have not been exploited yet. For example, the P_{es} problem can use predictive control command (e.g. H2 preview Saleh et al. [2010] or MPC Wang [2009]) to enhance the sources optimization. Also, the sub-optimality can be reduced by increasing the number of configuration, in particular for

the mobility client.

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