Energy Management for an Electric Vehicle Based on Combinatorial Modeling

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Abstract

This paper describes the process of electrical energy management and optimization in a multi-source system such as a Hybrid Electric Vehicle (HEV), running on a known mission profile. The purpose of the committed study is to minimize the consumption of the fuel used by one of the sources, to respect the different constraints related to the operating system and to meet the demand of the electrical motor powertrain. Lots of studies were led on a non-linear modeling of the problem giving suboptimal solution with important computation time. In this paper, a new combinatorial modeling is proposed to avoid such drawback. A computational study shows the benefits obtained using an exact combinatorial approach.

Key words: Energy Management; Hybrid Electric Vehicle; Non-Linear Modeling; Coin-Or Methods; Linearization; Combinatorial Modeling

1 Introduction

The multiple applications of electrical energy in the different domains of human activity are proving to be one of the technical evolution consequences. This is particularly the case of vehicles to which this form of energy allows a gain in terms of cost, autonomy, performance, and preserving the environment. These applications have even become a strategic and a technological challenge, so this energy, unlike fossil fuels, is a solution for the future because it is renewable, inexhaustible, available, and noiseless.

The energy chain of a Hybrid Electric Vehicle (HEV) is composed of at least two energy sources (fuel cells, photovoltaic panels, batteries, supercapacitors) with different characteristics (efficiency, energy losses, powers, capacity). The reversible sources as the battery and the supercapacitors, allow storing electrical energy when the vehicle brakes (transformation of the kinetic energy into electrical energy). In previous studies, electrical energy management was represented by a non-linear model, solved using methods such as dynamic programming [3][7], quasi-Newton method [4], or fuzzy logic [5]. The solutions then obtained are suboptimal and require significant computation times.

To improve the solution, a first attempt is proposed. It consists in using Computational infrastructure for Operations research methods (Coin-Or) [6] such as Interior Point Optimizer (IPOpt) applied to the nonlinear model to measure the quality of the solution obtained. However the major innovation made in this study was to develop a combinatorial modeling by using techniques for linearization and a discretization space of energy, to use the exact methods of operations research such as the Branch-and-Cut method in order to find a global optimum. Thus, the information related to the combinatorial model allow to define planes which reduce the search space and find an optimal solution with very restricted computation time.

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2 Description of the energy system

The energy chain of the vehicle concerned is composed of a Fuel Cell System (FCS) using hydrogen as a fuel; its energy is produced from the chemical reaction of hydrogen and oxygen. FCS is characterized by its efficiency and the efficiency of its auxiliaries: air compressor which represents 80% of the total energy consumed by the auxiliaries, temperature and humidification regulating pumps, connected to the distribution bus via a unidirectional converter. The energy chain also contains a storage system composed by a pack of supercapacitors connected in series and parallel, characterized by its energy losses function, which is connected to the bus via a bidirectional converter. A consumption source represents the powertrain demand.

The converter is an electronic module which delivers a current maintaining a regulated output voltage. It keeps the bus voltage to its reference despite voltage variations of the FCS and the supercapacitor. It is characterized by high efficiency ranging from 93% to 97% due to high quality of power electronics component.

The energy losses of the storage element $Loss_{se}$ (Figure 1) are calculated from efficiency of the supercapacitors η_{sc} and the converter η_{cvs}:

$$\eta_{se} = \eta_{sc}\eta_{cvs} \tag{1}$$

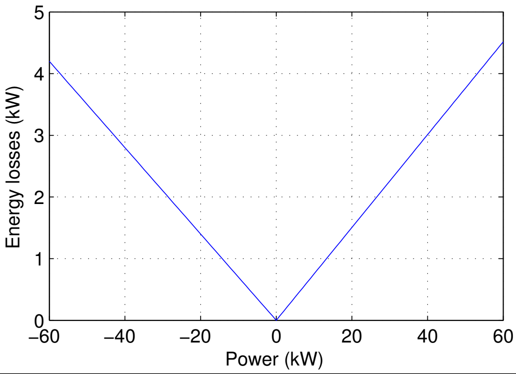

Fig. 1. Storage element energy losses

The FCS efficiency η_{fcs} is calculated from the efficiency of the fuel cell itself η_{fc}, the air compressor η_{air} and the converter η_{cvs}:

$$\eta_{fcs} = \eta_{fc}\eta_{air}\eta_{cvs} \tag{2}$$

The experiments showed that a maximum efficiency of the FCS, controlled in pressure, temperature and humidity is equal to 46% (Figure 2). By increasing the pressure in the cathodic compartment, the FCS voltage increases, this explains an increase of its performance. However, further increasing the pressure cathode, the power absorbed by the air compressor increases, which leads to decreasing the FCS performance. The efficiency is quite bad due to the low power of the compressor which has a very poor efficiency at reduced speed. Moreover, the FCS in such HEV is made with solid membrane with imposed nominal pressure.

3 Mathematical modeling

The objective is to minimize hydrogen consumption used by the FCS throughout the mission, while satisfying system constraints. Two mission profiles are proposed: the INRETS (National REsearch Institute on Transport and their Security) mission profile, which corresponds to the instantaneous power demand of an electric vehicle in urban areas (Figure 3), and the ESKISEHIR mission profile corresponding to the power demand of a tramway in Turkey (Figure 4).

In previous works, a non-linear model was developed [1][2] due to the characteristics of the different energy sources (FCS efficiency and energy losses of the storage element):

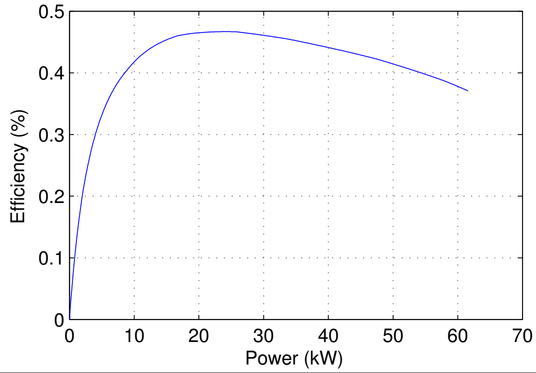

Fig. 2. FCS efficiency

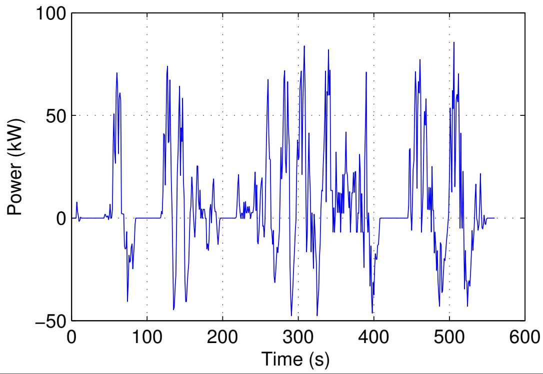

Fig. 3. INRETS mission profile

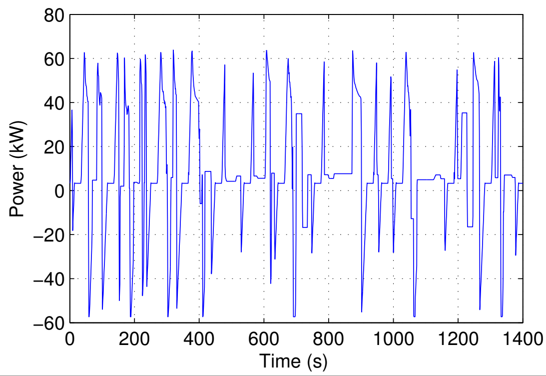

Fig. 4. ESKISEHIR mission profile

$$\min \sum_{t=1}^{T} P_h(t)\Delta t \equiv \min \sum_{t=1}^{T} \frac{P_{fcs}(t)}{\eta_{fcs}\big(P_{fcs}(t)\big)}\Delta t \tag{3}$$

$$P_{fcs}(t) + P_{se}(t) = P_{req}(t) \qquad \forall t \in T, P_{req}(t) \geq 0 \tag{4}$$

$$P_{req}(t) \leq P_{se}(t) \leq 0 \qquad \forall t \in T, P_{req}(t) < 0 \tag{5}$$

$$P_{fcs}^{min} \leq P_{fcs}(t) \leq P_{fcs}^{max} \qquad \forall t \in T \tag{6}$$

$$P_{se}^{min} \leq P_{se}(t) \leq P_{se}^{max} \qquad \forall t \in T \tag{7}$$

$$SOC_{se}^{min} \leq SOC_{se}(t) \leq SOC_{se}^{max} \qquad \forall t \in T \tag{8}$$

$$SOC_{se}(t) = SOC_{se}(t-1) - \big(P_s(t)\Delta t\big) \qquad \forall t \in T \tag{9}$$

$$P_s(t) = P_{se}(t) + Loss_{se}\big(P_{se}(t)\big) \qquad \forall t \in T \tag{10}$$

$$SOC_{se}(T) = SOC_{se}(0) \tag{11}$$

The decision variables are: $P_{fcs}(t)$ power supplied by the FCS at each instant t; $P_{se}(t)$ power supplied/recovered by the storage element at each instant t; and SOC_{se} state of charge of the storage element at each instant t. Input parameters are defined in Table 1. Consequently, the meaning of the mathematical model is as follows:

- (3): The objective function is to minimize the hydrogen consumption used by the FCS; it can be also written using the FCS efficiency and its power provided.
- (4): Satisfy the powertrain demand when the vehicle is in traction.
- (5): Recovering all braking energy can force the FCS to operate at its poor efficiency.
- (6,7): Power limits related to the design of the energy sources.
- (8): Storage capacity of the storage element.
- (9): State of charge evolution of the storage element.
- (10): Energy losses of the storage element used to identify the real power $P_s(t)$ supplied/recovered by the storage element.
- (11): Reset the state of charge of the storage element at its initial level at the end of the mission.

Table 1
Input model parameters.

Input data	Value	Signification
$SOC_{se}(0)$	900 $kW.s$	Initial energy storable in the storage element
SOC_{se}^{min}	400 $kW.s$	Minimum energy storable in the storage element
SOC_{se}^{max}	1600 $kW.s$	Maximum energy storable in the storage element
P_{se}^{min}	-60 kW	Maximum power injected to the storage element
P_{se}^{max}	60 kW	Maximum power extractable from the storage element
P_{fcs}^{max}	70 kW	Maximum power extractable from the FCS
I_{fcs}	601	Number of the FCS operating points
J_{se}	120	Number of the energy losses function
Δt	1 s	Time stepsize
T	560 s	INRETS mission duration
T	1400 s	ESKISEHIR mission duration

4 Problem solving

Lots of methods were developed in previous works such as dynamic programming, quasi-Newton method and fuzzy logic. Their principle is briefly explained below. The solution given by each method is suboptimal and obtained after a large computation time due to the problem complexity.

4.1 Dynamic programming

Dynamic programming is a sequential combinatorial optimization method for the optimal solution research using the Bellman's principle. The idea is to discretize the time horizon in T points of Δt stepsize and the energy space of the storage element in N points of ΔE stepsize. The weakness of this approach on the energy management modeling is related to the choice of the discretization applied to the energy space of the storage element. By decreasing the number of possible states of charge of the storage element, part of possible solutions is eliminated with a strong possibility that the optimal solution belongs to this set. When the number of possible states of charge increases, it causes more choices and computation explosion to determine the optimal sequence that minimizes the criterion of hydrogen consumption [3]. For a discretization of the time horizon in $\Delta t = 1$ s and energy space of the storage element in $\Delta E = 1$ $kW.s$, the optimal solutions found for the two mission profiles are given in Tables 2 and 3.

Table 2
Results of INRETS profile.

Method	Hydrogen consumption	Computation time	$SOC_{se}(T) = SOC_{se}(0)$
Dynamic programming	10131 $kW.s$	22 *hours*	Yes
Quasi-Newton	8750 $kW.s$	23 *min*	Yes
Fuzzy logic	8359 $kW.s$	on-line	No

Table 3
Results of ESKISEHIR profile.

Method	Hydrogen consumption	Computation time	$SOC_{se}(T) = SOC_{se}(0)$
Dynamic programming	31826 $kW.s$	52 $hours$	Yes
Quasi-Newton	27542 $kW.s$	2.38 $hours$	Yes
Fuzzy logic	29802 $kW.s$	on-line	No

4.2 Quasi-Newton method

A quasi-Newton algorithm is an iterative method for solving nonlinear problems by using Karush-Kuhn-Tucker conditions and the computation of the Hessian and the second derivative of the Lagrangian. The local minimum is found when the gradient is zero. The solution found by this method using *fmincon* function integrated in Matlab Optimization toolbox, is a local optimum [4].

4.3 Fuzzy logic

The theoretical bases of Fuzzy Logic (FL) are established so as to be able to treat inaccurate variables of values between 0 and 1, according to their membership degrees in the verification of a condition, contrary to the Boole's logic in which variables must take values 0 or 1. The FL is an on-line method composed of three steps: Fuzzification, Rules definition, and Defuzzification. The solution given by this method violates the constraint of the final state of charge of the storage element because the optimization is instantaneous and does not take into account future requests. The difficulty consists in adjusting some tuning parameters off-line. Evolutionary algorithms (e.g., genetic algorithm) permits the adjustment of the position of the membership functions with large computation time.

In off-line optimization, the storage element is reloaded to its initial level. The solution quality provided by dynamic programming depends essentially of discretization stepsize, this is why the solution given by the quasi-Newton method is better and uses less computation time. By applying fuzzy logic which is an on-line optimization method, the final level of the storage element cannot be reset if the optimization ignores future demands. The solutions found using INRETS and ESKISEHIR mission profiles are suboptimal. Although this method is effective when the car mission profile is unknown, it requires some adjustments made off-line that can require significant computation time.

5 Proposed approach

5.1 Using Coin-Or methods

Interior Point Optimizer (IPOpt) [9] is an open source software package used to find a local solution of nonlinear programming problems, based on the computation of the gradient and the Hessian of Lagrangian. The constraints and the objective function can be nonlinear and nonconvex but they must be twice continuously differentiable. The hydrogen consumption on the INRETS profile is 10910 $kW.s$ and 31150.77 $kW.s$ for the ESKISEHIR profile. The computation times are very small, less than one second.

5.2 A new combinatorial modeling

The principle of this new modeling is to work with the original data without using the linear approximations of the objective function and the energy losses function. By using the FCS operating point $i \in I_{fcs}$ characterized by its efficiency $\eta_{fcs}(i)$ and its supplied energy $P_{fcs}(i)$, and the decomposition of the energy losses function $Loss_{se}$ (piecewise linear convex function) in a set of J_{se} independent linear functions, the new decision variables of the combinatorial modeling are:

- $X(t,i) \in \{0,1\}$: Activation or not of the operating point $i \in I_{fcs}$ at time t,
- $Y(t,j) \in \{0,1\}$: Activation or not of the energy losses equation $j \in J_{se}$ at time t,
- $P_{se}(t)$: Power supplied or recovered by the supercapacitor at time t,
- $SOC_{se}(t)$: State Of Charge of the supercapacitor at time t,
- $Elos_{se}(t)$: Energy losses by the supercapacitor at time t.

where I_{fcs} (resp. J_{se}) is considered as input data given by the manufacturer as a point table P_h, P_{fcs} (resp. P_s, P_{se}), or can also be identified on the test bench by choosing the number of input points.

The power losses of the storage element is a piecewise linear convex function:

$$Elos_{se}(t) = \alpha_j P_{se}(t) + \beta_j, P_{se}(t) \in [\gamma_j, \gamma_j^{'}] \tag{12}$$

with (α_j, β_j) the characteristics of the line j over the interval $[\gamma_j, \gamma_j^{'}]$. To avoid the polynomial approximation, the equation (13) is used:

$$Elos_{se}(t) = \max_{j=1}^{J_{se}} \alpha_j P_{se}(t) + \beta_j \tag{13}$$

where J_{se} is the number of linear functions and $j \in J_{se}$ its index. Knowing that max function is non-linear, this function can also be modeled by a system of linear equations using binary variables and a *big*-M constant:

$$Elos_{se}(t) \leq \alpha_j P_{se}(t) + \beta_j + M(1 - y(j,t)) \tag{14}$$

$$Elos_{se}(t) \geq \alpha_j P_{se}(t) + \beta_j \tag{15}$$

$$\sum_{j=1}^{J_{se}} y(j,t) = 1 \tag{16}$$

The final combinatorial modeling obtained is:

$$\min \sum_{t=1}^{T} \sum_{i=1}^{I_{fcs}} X(t,i) \frac{P_{fcs}(i)}{\eta_{fcs}(i)} \Delta t \tag{17}$$

$$P_{se}(t) + \sum_{i=1}^{I_{fcs}} X(t,i) P_{fcs}(i) = P_{req}(t) \qquad \forall t \in T, \forall i \in I_{fcs} \tag{18}$$

$$P_{req}(t) \leq P_{se}(t) \leq 0 \qquad \forall t \in T, P_{req}(t) < 0 \tag{19}$$

$$\sum_{i=1}^{I_{fcs}} X(t,i) = 1 \qquad \forall t \in T, \forall i \in I_{fcs} \tag{20}$$

$$P_{se}^{min} \leq P_{se}(t) \leq P_{se}^{max} \qquad \forall t \in T \tag{21}$$

$$SOC_{se}^{min} \leq SOC_{se}(t) \leq SOC_{se}^{max} \qquad \forall t \in T \tag{22}$$

$$SOC_{se}(t) - \big(SOC_{se}(t-1) + P_s(t)\Delta t\big) = 0 \qquad \forall t \in T \tag{23}$$

$$Elos_{se}(t) \leq \alpha_j P_{se}(t) + \beta_j + M(1 - y(j,t)) \qquad \forall t \in T, \forall j \in J_{se} \tag{24}$$

$$Elos_{se}(t) \geq \alpha_j P_{se}(t) + \beta_j \qquad \forall t \in T, \forall i \in J_{se} \tag{25}$$

$$\sum_{j=1}^{J_{se}} y(j,t) = 1 \qquad \forall t \in T \tag{26}$$

$$P_s(t) = P_{se}(t) + ELos_{se}(t) \qquad \forall t \in T \tag{27}$$

$$SOC_{se}(T) = SOC_{se}(0) \tag{28}$$

The additional or modified constraints are:

- (17): The objective function is to minimize the hydrogen consumption used by the FCS, written using the FCS operating points.
- (18): Satisfy the powertrain demand when the vehicle is in traction.
- (20): One FCS operating point is activated a each instant t.
- (24,25,26,27): Energy losses of the storage element.

5.3 Solving and results

The Branch-and-Cut algorithm [8][10] used to solve energy management model is an exact method for combinatorial optimization which is generally employed for solving exactly NP-hard problems. It integrates cutting planes to accelerate the optimization process and branch and bound methods. The combinatorial model proposed is solved by the Branch-and-Cut method using *IBM-Ilog Cplex 12.4*. The result minimizes the hydrogen consumption used by the FCS, by running it at maximum efficiency points. For this, unnecessary operating points can be eliminated by introducing specific cuts: $\sum_{i=1}^{I_{fcs}} x(i,t)P_{fcs}(t) \leq P_{fcs}^{lim}$, where P_{fcs}^{lim} belongs to the set of powers with maximum efficiency.

Table 4
Branch-and-Cut Results.

Mission profile	Hydrogen consumption	Computation time	$SOC_{se}(T) = SOC_{se}(0)$
INRETS	8750 $kW.s$	2.6 s	Yes
INRETS	8269 $kW.s$	12.43 s	No
ESKISEHIR	27542 $kW.s$	1.54 min	Yes
ESKISEHIR	26954 $kW.s$	2.4 min	No

The optimization is realized off-line and the solutions obtained using branch-and-cut method on the combinatorial model are optimal and require very little computation time (see Table 4). In particular, the computation time were dramatically reduced. These benefits must be linked to both the proposition of a combinatorial modeling and the use of an efficient integer programming. To compare the results with the different methods previously developed, resetting the final charge level of the storage element is an optional constraint.

The simulations show that the hydrogen consumption and the computation time are lower with our approaches (values to be compared with those of Tables 2 and 3). In particular, the computation times were dramatically reduced. These benefits must be linked to both the proposition of a combinatorial modeling and the use of an efficient integer programming solver. The results obtained on the ESKISEHIR profile by selecting the constraint of the final state of charge of the storage element give the evolution functioning of the FCS and the storage element.

The FCS provides power to meet the demand of the powertrain and maintaining the state of charge of the storage element between its bounds. To minimize the hydrogen consumption, the FCS works most of the time at its maximum efficiency points (Figure 5).

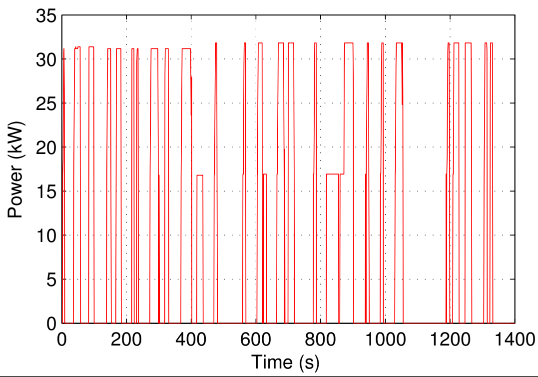

Fig. 5. FCS power provided

The storage element recovers power when the vehicle brake and provides it in the traction mode. Sometimes, it is better to recover a portion of the braking power to permit the FCS to operate at its maximum efficiency points (Figure 6).

The energy level of the storage element respects the capacity constraint and it is recharged to its original level at the end of the mission, allowing processing other missions in the same conditions (Figure 7).

The energy losses of the storage element (Figure 8) correspond perfectly to its curve of energy losses, which confirms the correctness of the results obtained and the quality of the representative model.

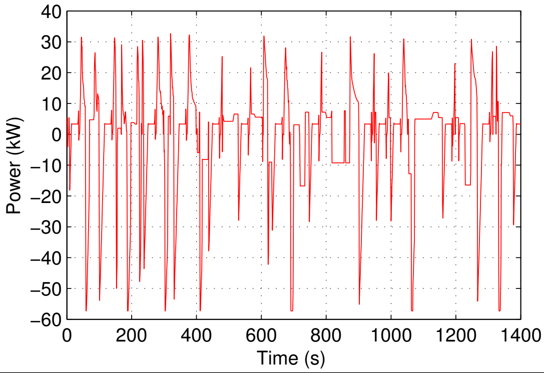

Fig. 6. Storage element power provided/recovered

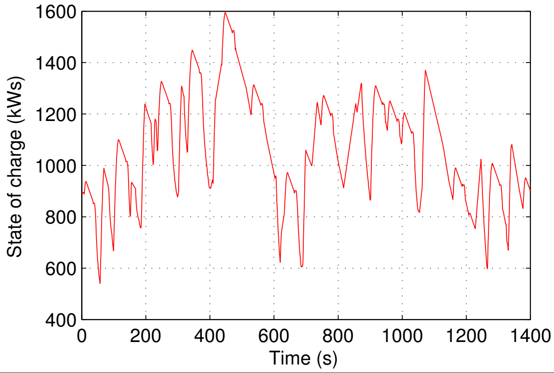

Fig. 7. State of charge of the storage element

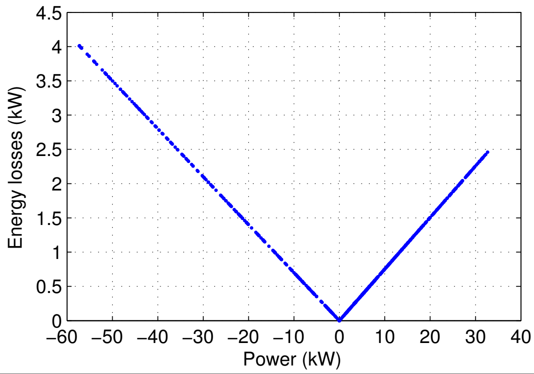

Fig. 8. Energy losses of the storage element

6 Conclusions

Transport is responsible for a large part of the CO_2 emissions from the fuel combustion. To minimize this effect, the hybrid vehicle has been industrialized using different energy sources, and it is necessary to manage the power distribution of its sources off-line (e.g., the case of a tramway whose mission profile is known). Several methods have been developed to provide solutions but with very large computation times. However, to avoid long waits in case of transport network problems, it is best to restart the vehicle in a very short term.

The combinatorial modeling developed in this paper allows using operations research techniques in the electrical engineering domain and to compare the results obtained with the methods previously developed. Other simulations were performed on long mission profiles. The solution obtained by applying the combinatorial model is much better in terms of quality and computation time. More numerical experiences should be carried out in the short term to further validate our model and solution method. More numerical experiences should be carried out in the short term to further validate our model and solution method.

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