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Efficiency Optimization Approaches for Hybrid Electric Vehicles

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***Abstract*—Currently, the exploitation and use of electric and/or hybrid vehicles have developed rapidly. Their concepts, combining two or more energy sources: thermal, electric or other, pose various constraints on the vehicle's energy fluencies management. For which, it is the key factor in maintaining the best energy efficiency. The idea here is therefore to contribute to it. This work thus underlines the interest in optimizing energy management in a hybrid-powered electric vehicle. It also emphasizes the implementation of optimization strategies by artificial neural networks and fuzzy logic. Several simulation results are presented accordingly. These results showed that the use of optimization by fuzzy neural networks adapts very well to improving the energy efficiency of the hybrid-powered electric vehicle.**

Keywords*—Hybrid-powered Electric Vehicle, Inwheel motors, Energy conversion efficiency, Fuzzy neural network, Optimization.

I. INTRODUCTION

Improving the energy efficiency of a system is topical. In hybrid electric vehicles, various strategies have been proposed to contribute to this improvement. These strategies include: reducing CO_2 production and fuel consumption through internal combustion engines, setting up a battery management system, and improving its performance [1] [2].

For this, it is necessary to review the arrangement of energy exchanges in the vehicle. Hence, our contribution to the optimization of the energy efficiency of said vehicle will call for the improvement of the system's energy management. The energy efficiency's problem of a series hybrid-electric vehicle can be formulated as a constrained optimization problem. In [3], an energy management system is applied to a parallel hybrid electric vehicle is proposed. In our case, we will try to optimize the energy efficiency of a series hybrid vehicle.

In addition, several optimization strategies have been the subject of much research, including the use of simulated annealing, genetic algorithms, dynamic programming and analytical optimization [4] [5] [6].

In the present work, we have opted for energy optimization through particle swarm optimization (PSO) [7], dynamic programming [8], and the use of neural networks based on fuzzy logic [9] [10].

In this part, we will first highlight the power distribution in the studied system. We will try, thereafter, to dissect the use of the dynamic optimization with the systems, while detailing the possibilities, followed by the off-line and on-line energy management of a system. All this will be accompanied by the implementation of the proposed optimization strategies.

II. ENERGETIC DESCRIPTION OF THE ARCHITECTURE AND GENERAL FORMULATION OF THE PROBLEM

The studied architecture consists of a heat engine coupled to a generator to form the heat engine. It produces an electric current distributed on the vehicle's electrical power network via its voltage rectifier. Traction of the vehicle is only ensured by two electric machines, each integrated into the wheels of the vehicle. In the case of thermal motorization, the generator's rotation speed is adapted to the thermal engine's speed by a reduction gear [1] [11]. For a request for power to the driving wheels, a traction chain's supervisor sends a power command ***u*** to the battery. The internal combustion engine supplies the difference in power between the battery's power supply and the load formed by the power at the wheel and auxiliaries.

A. Energy balance of system

The sum of the powers formed by the internal combustion engine, the PV generator and the battery must satisfy the

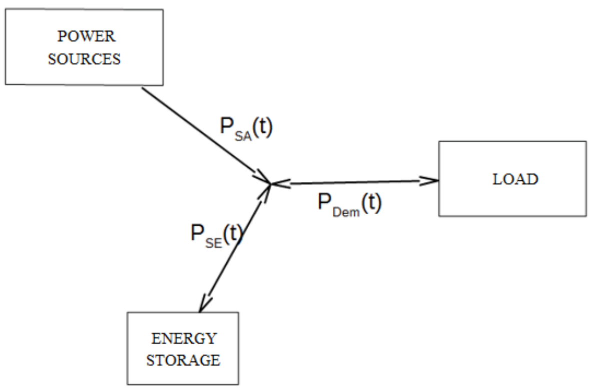

Fig. 1. Representation of the power balance of the series hybrid traction chain studied

necessary power requested by the demand to insure the vehicle's well working. Fig. 1 illustrates the power exchange's principle, translated by relation 1.

It is established from a simple electrical node because there is no mechanical coupling between the combustion engine and the wheels. Only electric motors provide traction for the vehicle.

B. Expression of the power of the whole

It is represented by the following relationship:

$$P_{SA}(t)+P_{SE}(t)=P_{dem}(t) \quad (1)$$

Where, P_{SA} is the power produced by the power sources; P_{SE} is the electrical power produced by the hybrid power supply; P_{dem} is formed by the sum of the electric power at the terminals of the electric machine's inverter.

The energy storage's power is expressed from the relation on the electrical node, i.e.:

$$P_{SE}(t)=P_{dem}(t)-P_{SA}(t) \quad (2)$$

1) The torque and speed of the power components:

The various power components of the traction chain are characterized by performance maps. To identify at each instant the efficiency's value into consideration, the torque and the speed of the considered component must be determined:

- for the heat engine (C_{mth}, ω_{mth}).
- for the generator (C_{gen}, ω_{gen}).
- for an electric traction machine, (C_{me}, ω_e), which is mechanically integrated into the wheels.

2) Case of the power supply based on a photovoltaic generator:

We consider that the photovoltaic generator based power supply will be used to charge and/or recharge the battery in the presence of strong sunlight. The modeling of said power supply, comprising block of photovoltaic modules, a Boost converter, a load (Battery), as well as a control block has been studied in [12]. Such system was adopted with the aim of giving the vehicle more autonomies in a fuel shortage's event.

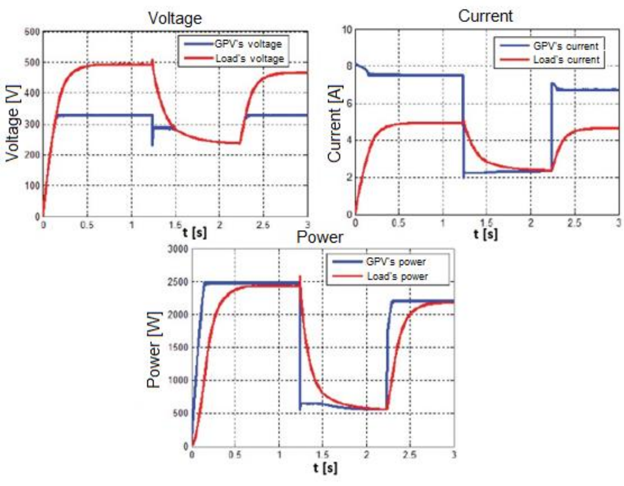

Fig. 2. Response of the photovoltaic generator to a variation in sunshine

Fig. 2 below shows an example of the response of the GPV under the effect of the variation in sunshine, pollutant emissions.

3) System operating modes:

As equation 1 shows, at any instant of a mission profile, the two energy sources must satisfy the power demanded by the electric motorization. Then, the energy management program will serve as a precision on the proportion of energy from each source to ensure the demand. In this topology, the powers, expressed as a function of time t, are also represented by a power profile to be supplied. Moreover, from this equation too, we can specify three working mode including: in start-up mode, in normal mode and in recovery mode [4] [6].

As for the start-up mode, it consists in systematically cutting off the internal combustion engine, since at that time there is no power demand. It is characterized by short stops and will allow the heat engine to be restarted quickly. The normal mode contains the acceleration and cruising functionalities of the system. In acceleration mode, the system will call on the internal combustion engine to satisfy the demanded power at his level. Switch to cruise mode is due to the fact that the minimum power demand were followed. It is possible to cut off or operate the internal combustion engine under the constraint of the battery's states of charge [3].

If the power required by the motorization is negative (braking or deceleration), only the battery will ensure the recovery of this energy in order to store it for future use.

C. Problem's formulation

This is to minimize fuel consumption while achieving optimum power distribution between the various elements of our system over the entire mission.

A constrained dynamic optimization problem is often modeled by the following set of equations [5] [6]:

$$\begin{cases} \dot{x}(t)=f\left(x(t),u(t),t\right) \\ j(t)=\int_{t_0}^{t_f}\gamma\left(x(t),u(t),t\right)dt \\ \psi\left(x(t),u(t)\right)=0 \\ \phi\left(x(t),u(t)\right) \end{cases} \quad (3)$$

Where, ***x(t)*** forms the state variables, ***u(t)*** represents the control variables, ***j(t)*** is used to evaluate the cost function between t_0, the path's start and ***tf***, the end and with the constraints imposed on the system by the functions ***ψ(t)*** and ***φ(t).***

We have proposed to break up the problem into: state equation, cost criteria, boundary conditions, instantaneous constraints and state constraints. In our system, the state variable, ***x***, represents the state of the energy storage element. The equation of our system's dynamics [8] [13], noted *E(t)*, is written by:

$$\dot{E}(t)=-P_S(t) \quad (4)$$

Where, in discharge, $P_S(t)$ is given by (5):

$$P_S(t)=\frac{P_{SE}(t)}{\eta_{ES}\left(P_{SE}(t)\right)} \quad (5)$$

And in charge,

$$P_S(t)=P_{SE}(t)\cdot\eta_{ES}\left(P_{SE}(t)\right) \quad (6)$$

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1) Cost criteria

It is, here, formed by the instantaneous consumption of fuel, ***j(t)***, which depends on the power supplied by the PSA combustion engine and the total efficiency of the combustion engine, η_{MTh} . Its expression is given by:

$$J_{Cf} = j(t) = \int_{t_0}^{t_f} \gamma\left(x(t), u(t), t\right) dt \qquad (7)$$

where,

$$\gamma\left(x(t), u(t), t\right) = \frac{P_{SA}(t)}{\eta_{Mth}\left(P_{SA}(t)\right)}. \qquad (8)$$

Then, various constraints are defined. The first constraint is related to the limits of the state of charge, SOC, of batteries storage and which is given by:

$$\Delta_{SOC} = SOC_f - SOC_i = 0 \qquad (9)$$

Here Δ_{SOC} symbolizes the difference in the states of charge at the start and at the end of the mission.

The second constraint which forms the instantaneous constraints of the equality type is specified by the relation:

$$P_{SA}(t) + P_{SE}(t) - P_{dem}(t) = 0 \qquad (10)$$

2) Inequality constraints

These constraints set maximum and minimum bounds on all the traded powers and the energy levels that can be achieved. These expressions are given by the relations:

$$\begin{cases} P_{SEMin} \le P_{SE}(t) \le P_{SEMax} \\ P_{SAMin} \le P_{SA}(t) \le P_{SAMax} \\ SOC_{Min} \le SOC(t) \le SOC_{Max} \end{cases} \qquad (11)$$

Where, P_{SEMax} represents the maximum power that the storage element can provide and P_{SEMin} is the minimum power that this element can approach, all this, at a given instant; The minimum and maximum powers provided by the power supply system are represented respectively by P_{SAMin} and P_{SAMax} ; State of Charge (SOC) represents the amount of energy remaining in the storage system expressed as a percentage of maximum energy

Thus, subsequently, several optimization methodologies result from this are to find, not only the best distribution of power in the system but also to estimate the fuel economy for a given mission profile.

These energy management laws are formed by algorithms making it possible to solve this optimization problem.

III. ENERGY OPTIMIZATION STRATEGY AND IMPLEMENTATION

The optimization of a dynamic system is based on the idea of bringing significant improvements to the static and dynamic behavior of a given system, stability, reference tracking, presence of obstacles, etc.

Several optimization strategies exist but in this case, the optimization is based on the distribution of powers in the system according to the given mission profile.

A. Offline energy optimization

The global optimization problem is solved, either by using a dynamic programming approach which is based on Bellman's principle of optimality [8] [13], or on an optimal control based on the principle from the minimum. But in this case, dynamic programming were used.

So, this study is focused on the minimization of the cost function, formed in equation 7. In discrete time, we write the formulation of the problem as follows:

- The objective is the minimization of the cost function which is governed by the equation:

$$\min J_{Cf} = \min \sum_{i=0}^{n} \frac{P_{SA}(i)}{\eta_{Mth}\left(P_{SA}(i)\right)} \qquad (12)$$

- The constraints are formed by the set of the following equations:

$$\begin{cases} P_{SA}(i) + P_{SE}(i) - P_{dem}(i) = 0 \\ P_{SEMin} \le P_{SE}(t) \le P_{SEMax} \\ P_{SAMin} \le P_{SA}(t) \le P_{SAMax} \\ SOC_{Min} \le SOC(t) \le SOC_{Max} \end{cases} \qquad (13)$$

B. Online energy optimization

Offline energy management methods help to achieve optimal fuel consumption. But the hypothesis on the a priori knowledge of the required power cycle and the associated calculation times pose a problem for embedding these methods directly in a vehicle [11].

Several online optimization methodologies can be developed, namely, online optimal order passing, rule-based management [10], instantaneous optimization strategy and fuzzy logic exploitation [9].

1) Stateflow control technique :

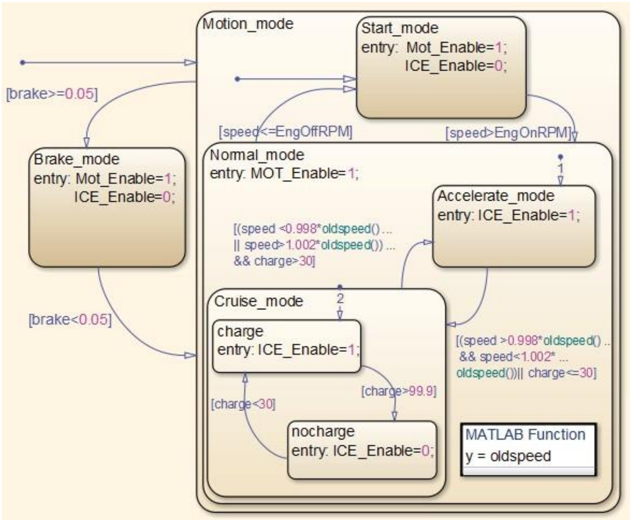

Fig. 3. Energy management by StateFlow under Matlab / Simulink

The simplest approach to perform energy management between the different elements of the vehicle is the use of Stateflows as shown in Fig. 3.

The current speed of the vehicle, the position of the brake pedal and the state of charge of the battery form the parameters taken into consideration to control the flow of energy in the system.

2) Particle Swarm Optimization (PSO)

The second part is the object of the implementation of the system based on Optimization by Particle Swarm. It is often formed by an evolutionary algorithm prompting a population

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of candidate solutions to develop an optimal solution to the problem [14] [15].

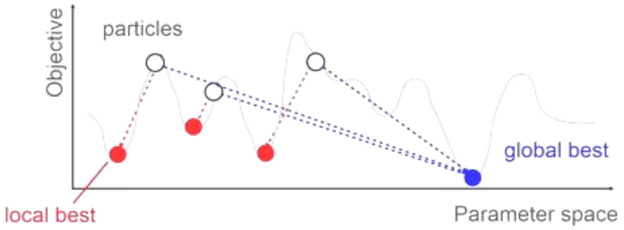

Fig. 4. Movement structure of particles

Its application is based on the movement of a particle which is often influenced by an inertial component, a cognitive component and a social component.

3) Optimization based on fuzzy neurons :

Various associations of neuro-fuzzy methods and architectures have been developed since 1988. The ANFIS architecture represents a fuzzy inference system implemented in the context of adaptive networks. Its Hybrid learning procedure allows refining the fuzzy rules obtained by human experts to describe the input-output behavior of a complex system [16] [17].

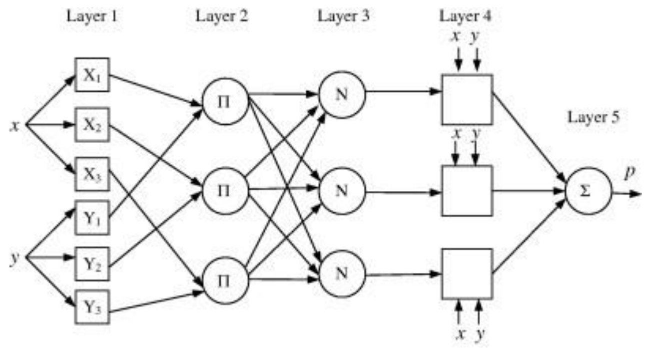

Fig. 5. The ANFIS's architecture

In trajectory tracking, this model gives very good results in nonlinear approximations, dynamic controls and signal processing. In this study, we limited ourselves to the use of the ANFIS method, because it lends itself best to our application.

IV. SIMULATION RESULTS AND INTERPRETATIONS

After modeling the system under Matlab/Simulink, the following results, for a personalized mission profile, are obtained.

By analyzing the curves below, it can be noticed that the displacement speed (the measurement) always manages to follow the reference speed (the demand). Namely, at the instant t = 20s when the vehicle changes gear, the battery compensates for the power demand $\boldsymbol{P_{dem}}$ of the motorization, through P_{SE}. At t = 80s, where the vehicle is in acceleration, the battery still try to satisfy the request.

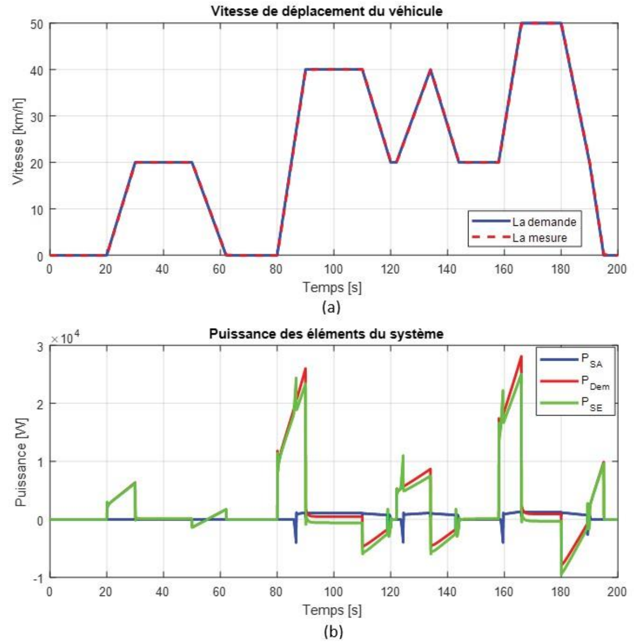

Fig. 6. Series HEV simulation results: (a) Vehicle travel speed, (b) Powers provided by each system element

But at t = 87s which the shift's speed outrun the limit of 30km/h, the internal combustion engine starts up and supplies the difference in power between the battery and the electric engine (Fig. 6) through P_{SA}.

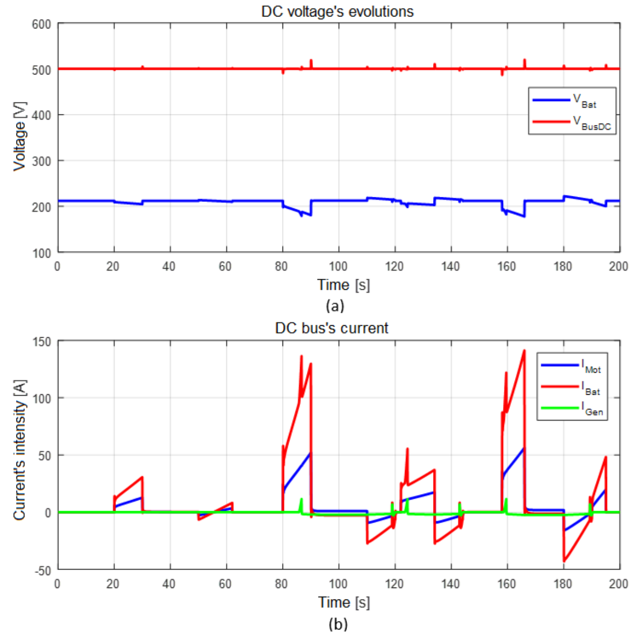

Fig. 7. Serial HEV simulation results: (a) The voltages, respectively, at the bus terminals and the battery, (b) The current intensities at the level of the electric motorization, the generator, and the battery

Throughout the journey, following various changes in demand, the three key elements of our system always try to satisfy the power demanded by the electric motorization.

Fig. 7(a) shows good stability of the DC bus voltage of the system compared to the voltage at the battery terminals, which shows a drop according to the importance of the power of the battery load to be compensated: V_{BusDC} = 500[V].

Moreover, because of an almost constant battery voltage, the demand for power causes an increase in the intensity of the current at its output, as illustrated in Fig. 7(b).

This increase has an effect on its state of charge.

Indeed, at the beginning, the battery charge was maintained at 100%. But a decrease as soon as the compensation comes into play is observed (Fig. 8(b)). It may be said that the system, at the moment, operates in pure electric mode.

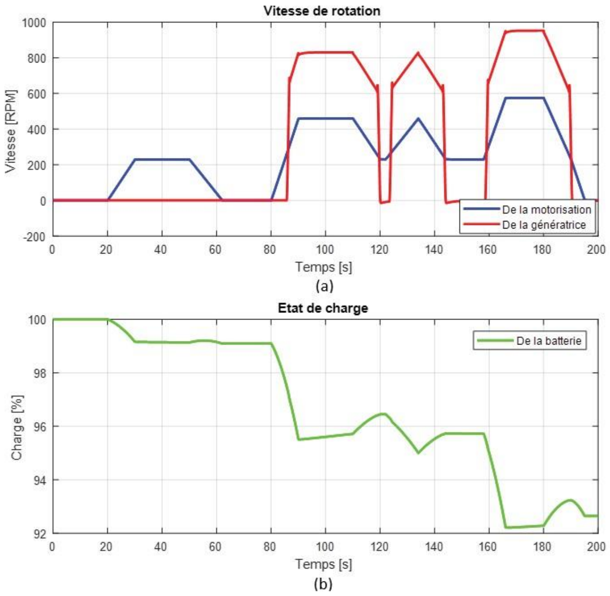

Fig. 8. Serial HEV simulation results: (a) The rotational speed of the brushless motor and the permanent magnet synchronous generator, (b) The evolution of the state of charge of the system battery

The internal combustion engine's start is always marked by a current peak at the battery's level.

This increase in power is well noticed at the state of charge's level of the battery which decreases to 95.5% but which recovers quickly in the presence of the internal combustion engine.

This means that the vehicle switches to hybrid mode, where the internal combustion engine not only meets the demand but also tries to restore the battery's state of charge.

These figures also show that the battery tries always to recover as much energy as possible as soon as opportunities arise, namely at times t = 50s, t = 110s, t = 134s and t = 180s.

At all these times, the vehicle goes into recovery mode and the rotation speed of the internal combustion engine decreases and stops as soon as the electric engine's rotation speed stabilizes. All of this can be visualized in Fig. 8.

V. DISCUSSIONS

It may be remembered that the objective of the present study is to improve the energy efficiency of the vehicle electric powered hybrid where the approach on decreasing fuel consumption has been adopted.

Table 1, below, summarizes the results of our contribution to the optimization of the energy efficiency of an electric vehicle hybrid-powered and with two-wheel drive (series hybrid electric vehicle type).

TABLE I. COMPARISON OF THE AVERAGE CONSUMPTION OF THE STUDIED SERIES HYBRID POWERED ELECTRIC VEHICLE

Consumption (l/ 100 km)	Cycle Urban	Cycle Extra -urban	Cycle NEDC	Cycle other
Journey time (s)	780	400	1180	200
Distance traveled (km)	4.052	6 , 955	11 , 007	2 , 02
Speed mean (km/h)	18 , 7	62 , 6	33 , 58	41 , 5
Conso . avg . stateflow (l/100km)	2 , 93	4 , 65	4 , 02	2 , 99
Conso . avg . PSO (l/100km)	2 , 81	4 , 59	3 , 96	2 , 95
Conso . avg . DP (l/100km)	2 , 79	4 , 41	3 , 92	2 , 924
Conso . avg . ANFIS (l/100km)	2 , 65	4 , 21	3 , 83	2 , 68

Of the four different types of rolling cycle proposed, these conclusions can be mentioned:

- optimization by stateflow demonstrates performance at 3.65l/100km on average,
- that based on PSO evokes, on average, 3.57l/100km of autonomy,
- the dynamic programming makes it possible to obtain a range of 3.51l/100km,
- the use of optimization based on the neuro-fuzzy system guarantees an average range of around 3.34l/100km.

VI. CONCLUSION

This paper aims to the optimization of series hybrid-powered electric vehicle performances. It began with an energy balance of the system, then, followed by introduction of all optimization strategies. Neuro-fuzzy optimization systems which encompass the performance of neural and fuzzy optimizations, have been used in order to give best results possibilities.

Following the comparison of these results, it can be concluded that the proposed system optimization allows to obtain a reduction in the average fuel consumption of the vehicle for all the proposed driving profile while ensuring the proper functioning of the system.

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