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Optimal Power Sharing Control of the Hybrid Energy Storage System of an Electric Vehicle Along a Standard Driving Cycle

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Abstract: The paper presents a strategy of energy loss minimization within a hybrid energy storage system of an electrical vehicle, composed by a battery and a supercapacitor. The optimization of the power sharing between these energy storage devices is performed for the New European Driving Cycle, using the Particle Swarm Optimization algorithm. The minimum energy storage required to pass through the driving cycle is taken into account as a time-variable constraint during the optimization. The dimension of the search space increases with the dimension of the optimization vector, which has to be kept low in order to keep the complexity of the problem manageable. It is shown, that the subdivision, and piecewise optimization of the driving cycle improves the result by means of relaxation of the constraint represented by minimum level of the required energy storage.

Keywords: Particle swarm optimization, hybrid energy storage system, electric vehicle, constrained optimization, New European Driving Cycle.

1. Introduction

In order to take advantage of the high energy storage capability of the batteries and high power capability of the supercapacitors, in electric vehicles these energy storage devices are combined into Hybrid Energy Storage Systems (HESS) [4] [7], [14]. An energy management algorithm has to be implemented to determine the optimal power sharing between the battery and the supercapacitor in order to minimize the energy losses and to extend the battery life cycle [9], [12], [13].

Due to the complexity of the optimization problem, the stochastic Particle Swarm Optimization (PSO) method is a good candidate for solving this task. There is a vast literature on PSO applying different methods for handling the constraints [2], [3], [5], [6], [10], [11].

In [16], [17] we introduced a constrained particle swarm optimization (PSO) algorithm [15], [18], [19] to minimize the energy losses of a HESS from an electric vehicle, for a simple driving cycle. In this paper an extension of the PSO is presented for the standard New European Driving Cycle (NEDC) [20].

2. The Optimization Problem

The model considered for the simulation and optimization of the electrical energy management is shown in *Fig. 1*. The hybrid energy storage system consists of a battery, a supercapacitor and the bidirectional power electronic converters connecting them to the same DC busbar, and providing the possibility of power sharing between the storage devices. Energy exchange between the battery and the supercapacitor has not been considered in this study.

The instantaneous electrical power requirement is derived from the instantaneous acceleration and speed along the driving cycle, the vehicle parameters, and the electrical efficiency of the HESS. In this study, the converter and electric drive losses have been omitted in order to emphasize the effect of the losses in the storage devices.

In the model, the battery voltage u_{BAT} is constant, while the internal resistance r_{BAT} depends on its state of charge *SOC* [1], [8], [11]. The internal resistance r_{SC} of the supercapacitor is constant, while its voltage u_{SC} varies with its state of energy *SOE*. The HESS parameters are shown in *Table 1*.

The vehicle model parameters used for simulation, specified in *Table 2*, correspond to a Tesla Model 3. However, the electrical energy storage devices and their initial charge have been chosen to limit the vehicle range close to the driving cycle length. Thus, the capacity of the battery is 120% of the energy needed to pass through the NEDC driving cycle, and its initial SOC is 83.3%. The energy storage capacity of the supercapacitor is 20% of that of the battery, and it’s initial SOE is 50%.

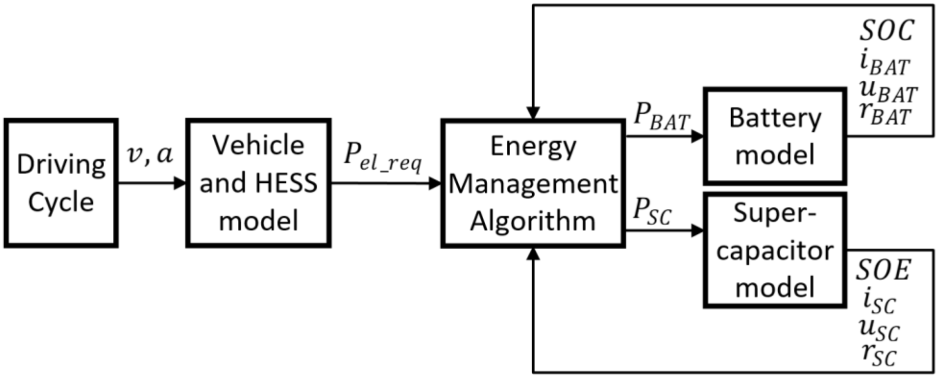

Figure 1: The block diagram of the model considered for the optimal control of the hybrid energy storage system [16].

Table 1: The parameters of the HESS, used for simulation.

Battery	Capacity	Q_{wh}	1.31 kWh
	No load voltage	u_{BAT}	800 V
	Initial state of charge	SOC_{init}	83.3 %
	Internal resistance at SOC=100%	$r_{BAT}\vert_{SOC=100\%}$	600 mΩ
	Internal resistance at SOC=50%	$r_{BAT}\vert_{SOC=50\%}$	1,05 mΩ
Supercapacitor	Capacity	C_{SC}	2.95 F
	Initial voltage	U_{SC_init}	566 V
	Internal resistance	r_{SC}	100 mΩ

Table 2: The parameters of the vehicle, used for simulation.

Mass of the vehicle	m	1611 kg
Air density	ρ_{air}	$1.202\ \frac{\mathrm{kg}}{\mathrm{m}^3}$
Aerodynamic drag coefficient	C_d	0.3
Maximum cross-section area	$A_{vehicle}$	2.22 m^2
Rolling resistance coefficient	$f_{vehicle}$	0.011

The optimization problem being studied is the optimal power sharing between the energy storage devices for minimum power losses in the HESS over a partition of the driving cycle. In the following, either a single partition (the entire driving cycle) or multiple partitions are being used, with subdivision of each partition into two segments. The optimization vector in each partition is formed by the power shares of the supercapacitor in the two subintervals, defined by (1), extended with the length of the first subinterval normalized to the length of the partition [16].

$$x(t) = \frac{p_{SC\_req}(t)}{p_{el\_req}(t)}. \tag{1}$$

Thus, the optimization task is to find is to find the extended optimization vector

$$\boldsymbol{x}_m^* = [x_1, x_2, \tau]_m = \arg\min_{\boldsymbol{x}^*}(W_{loss}), x_{1,2} \in [0,1], \tau \in [0,1] \tag{2}$$

In this way the dimension of the solution space is only 3, and the complexity of the problem is moderate [16].

In the following, this approach is applied to the whole driving cycle ("global optimization") and subsequently to each partition of the driving cycle ("piecewise optimization") to improve the result of the global optimization.

3. Global Optimization

The stochastic Particle Swarm Optimization (PSO) method is applied for the energy loss minimization in order to handle the problem complexity arising from the nonlinearity of the electric vehicle model including the HESS, the length of the driving cycle, and the multitude of local minima of the cost function W_{loss}.

The minimum energy storage required to pass through the driving cycle is taken into account as a time-variable constraint during the optimization.

Fig. 2 shows the vehicle velocity and acceleration along the New European Driving Cycle (NEDC). Based on the vehicle model, and on the estimated worst-case minimum of the hybrid energy storage system efficiency, the required mechanical and electrical power is calculated. The energy storage needed to pass through the driving cycle is derived as well. Further on, this storage requirement is reduced due to the optimization results, allowing for the relaxation of the minimum stored energy constraint.

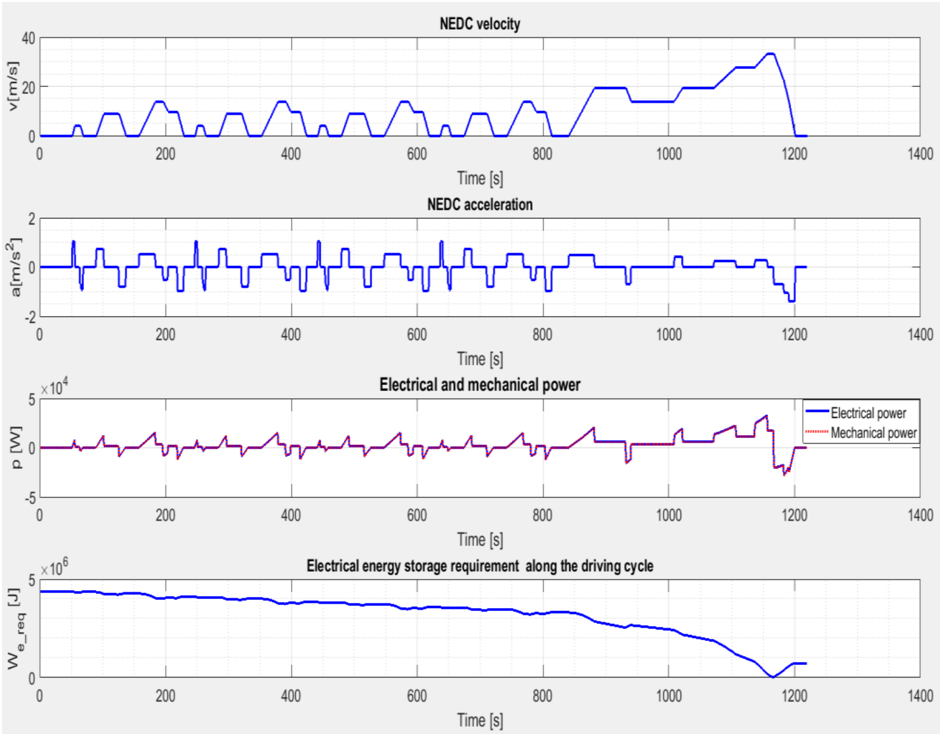

Figure 2: The NEDC velocity and acceleration (top); the power and electrical energy requirement along the driving cycle (bottom).

The flowchart of the global optimization algorithm is shown in *Fig. 3*. The energy storage is initialized according to the initial estimation of the electrical efficiency over the whole driving cycle. The particle swarm optimization is performed over the entire driving cycle using the optimization variable $[x_1, x_2, \tau]$ as shown in *Fig. 4*. Thus, the entire NEDC is subdivided into two time-intervals with constant power sharing ratio. Both the power sharing ratios and the time instant of the subdivision are elements of the optimization variable. The corresponding particle swarm optimization (PSO) algorithm is described in detail in [16]. The number of individuals in the swarm is 25, and a number of 8 constraints are applied during the optimization, including the minimum required energy storage, as a time function. The result of the optimization cycle is a better electrical efficiency, than initially assumed, thus the constraint regarding the required energy storage can be modified, extending the available search space, and thus improving the result of the next optimization cycle. A few such optimization cycles are performed until the efficiency increment using this method becomes negligible.

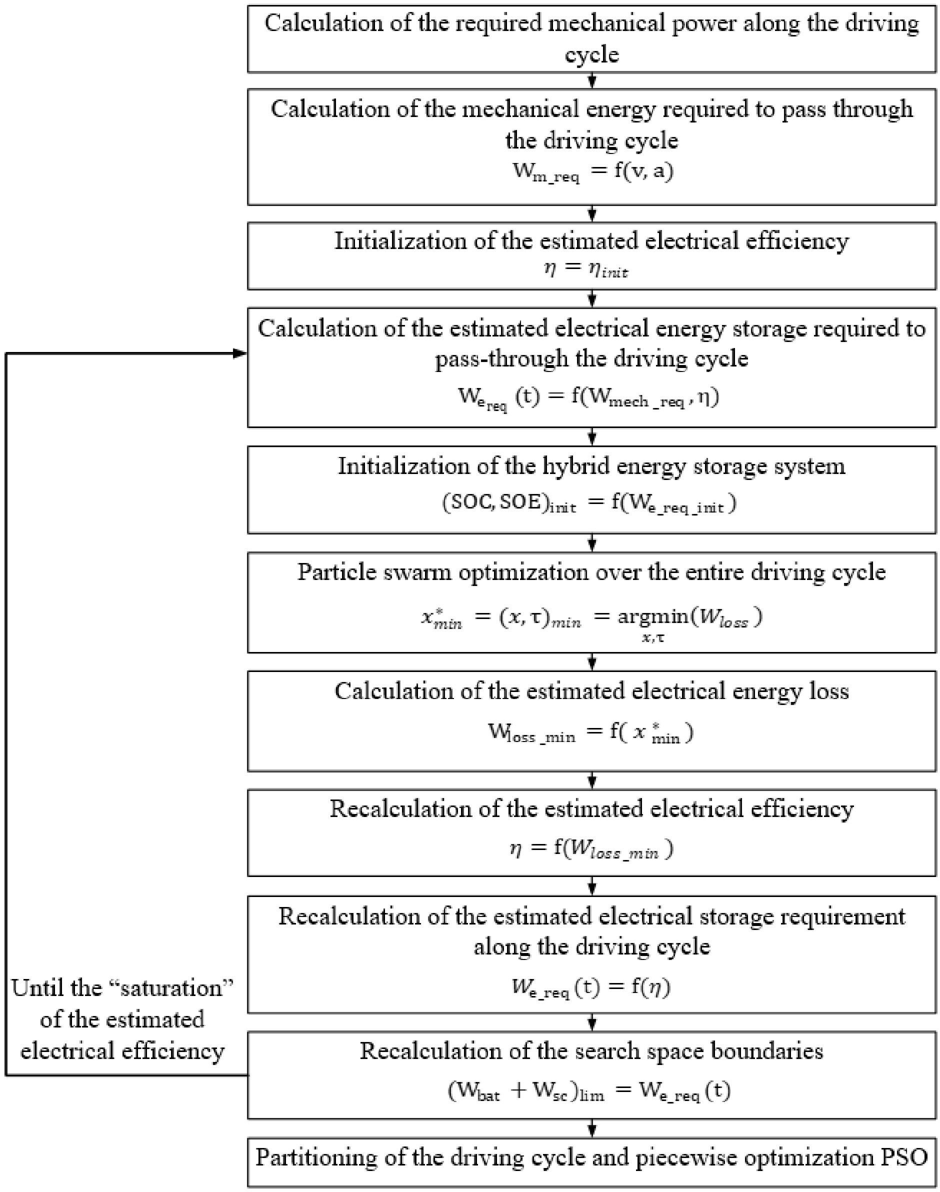

Figure 3: Flowchart of the global efficiency optimization algorithm.

Fig. 5 explains the evolution with the number of successive iterations of the required energy storage versus time, while *Fig. 6* illustrates the evolution of the estimated efficiency with the number of optimization cycles.

Further reduction of the HESS losses can be obtained by piecewise optimization over the partition of the driving cycle, as explained in the next section.

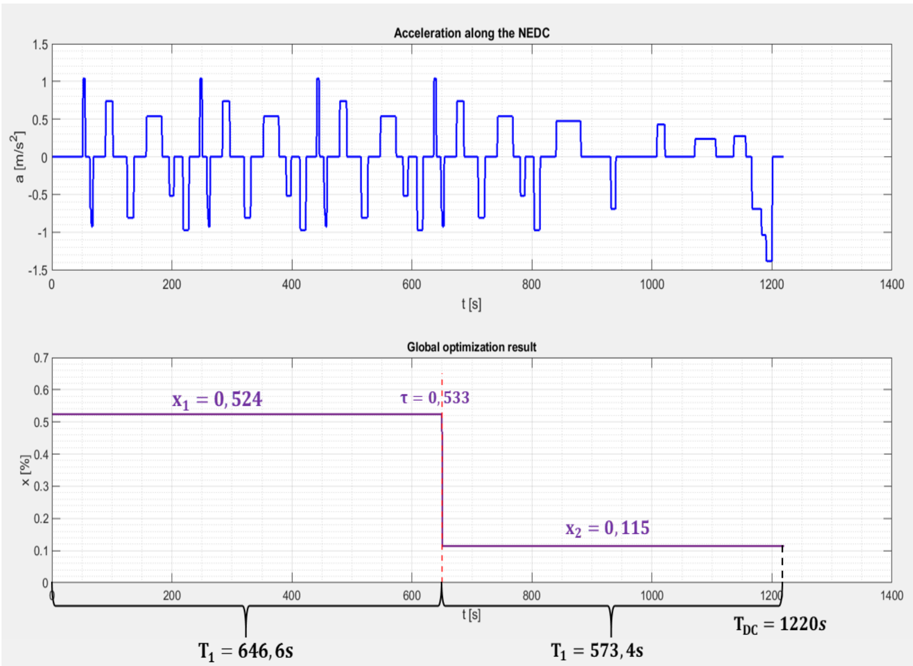

Figure 4: The NEDC acceleration profile (top), and the interpretation of the global optimization vector (bottom): $x^*_{\min} = (x_1, x_2, \tau) = (0.524, 0.115, 0.533)$.

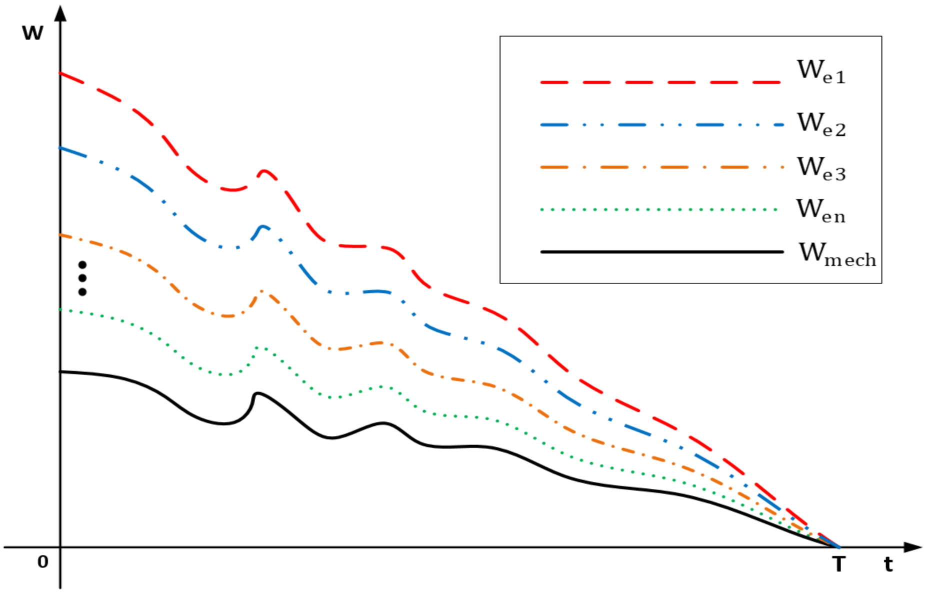

Figure 5: Variation of the energy storage requirement along the driving cycle with the number of iterations of the global efficiency optimization algorithm.

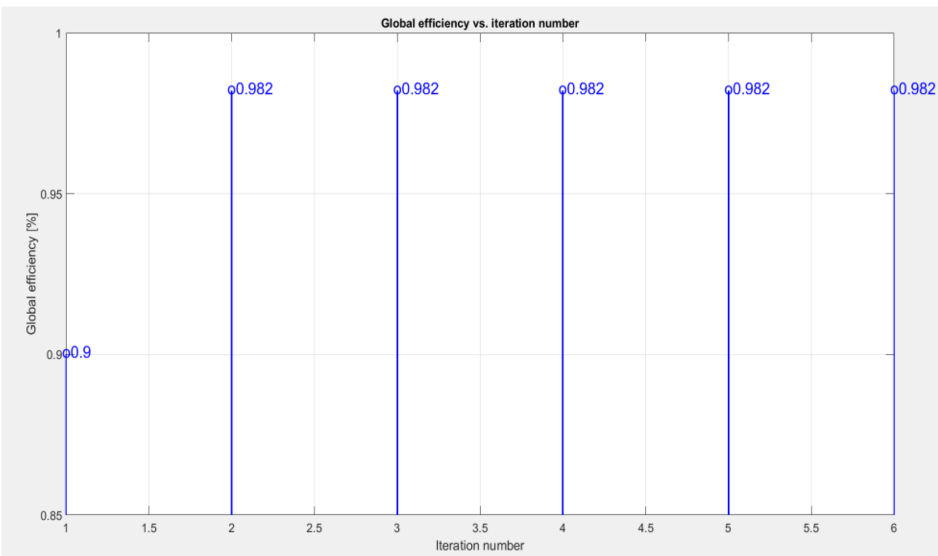

Figure 6: Variation of the global efficiency of the HESS vs. the number of global optimization iterations.

4. Piecewise Optimization

The dimension of the search space increases with the dimension of the optimization vector, which has to be kept low in order to keep the complexity of the problem manageable. It is shown, that the subdivision, and piecewise optimization of the driving cycle improves the result by means of relaxation of the constraint represented by the minimum level of the required energy storage.

The partitioning of the driving cycle can be made in multiple ways, and the advantages of each still have to be analyzed. During this study it has been observed that a partitioning at positive zero-crossing instants of the acceleration curve yields better results, than other trials (ex. at negative zero-crossings of the acceleration, at positive or negative zero-crossings of the required instantaneous power, or equidistant partitioning), consequently this is the approach used for the piecewise optimization, as shown in *Fig. 7*.

Each route section resulting from the partition is subdivided into two time-intervals, and the PSO algorithm is applied using the optimization vector formed by the power sharing ratios and the relative position of the subdivision. In the k-th partition, the optimization vector is $\boldsymbol{x} = (x_{1k}, x_{2k}, \tau_k)$, where $\tau_k = \frac{\boldsymbol{T_{1k}}}{\boldsymbol{T_{1k}+T_{2k}}}$, as shown in *Fig. 7*.

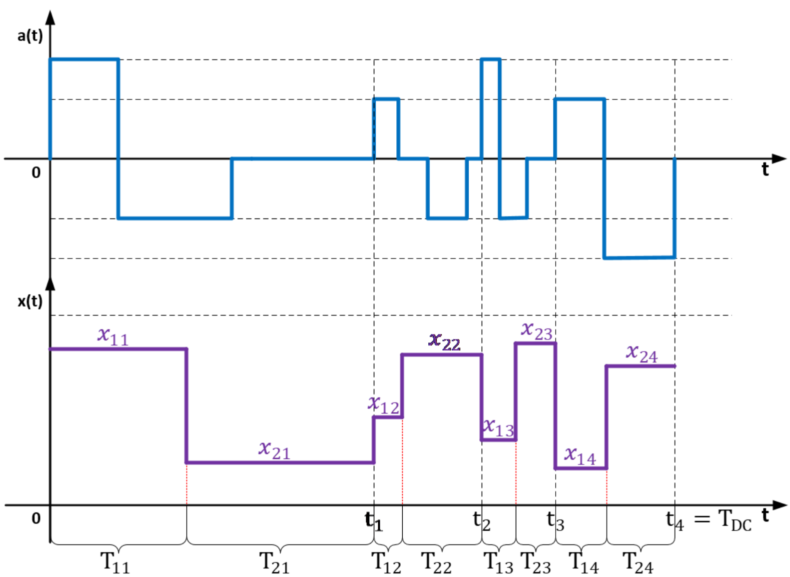

Figure 7: Illustration of the driving cycle partitioning and the optimization vector components along different route sections.

The flowchart of the piecewise optimization algorithm is shown in *Fig. 8.*
The energy saving ΔW_{es_k} obtained along the k-th route section is subtracted from the required energy storage in the $(k+1)$-th route section, thereby extending the available search space. This principle is illustrated in *Fig. 9*, where $W_e(t)$ is the energy consumption estimated using the efficiency obtained by global optimization, while $W_e^*(t)$ is the energy consumption obtained by piecewise optimization, updating the energy storage requirement after each route section.

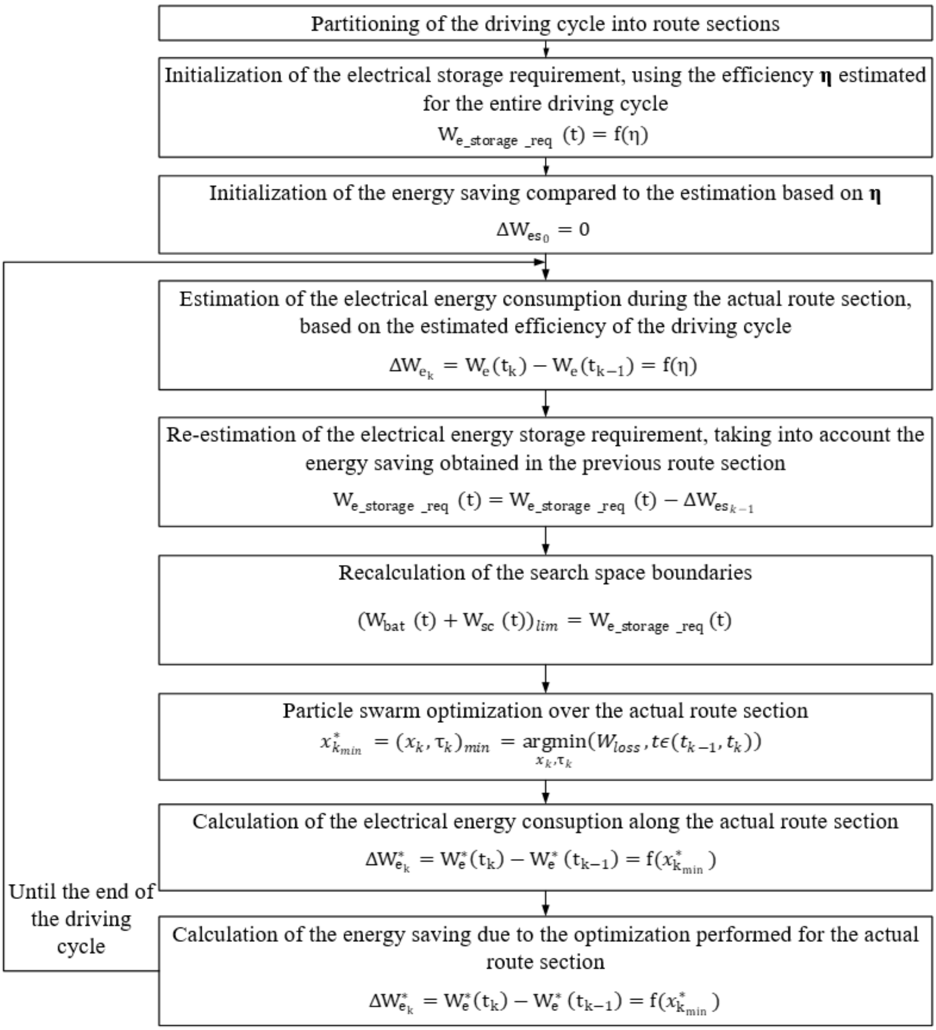

Figure 8: Flowchart of the piecewise optimization algorithm, which extends the search space of each route section due to the "energy saving" from the previous section.

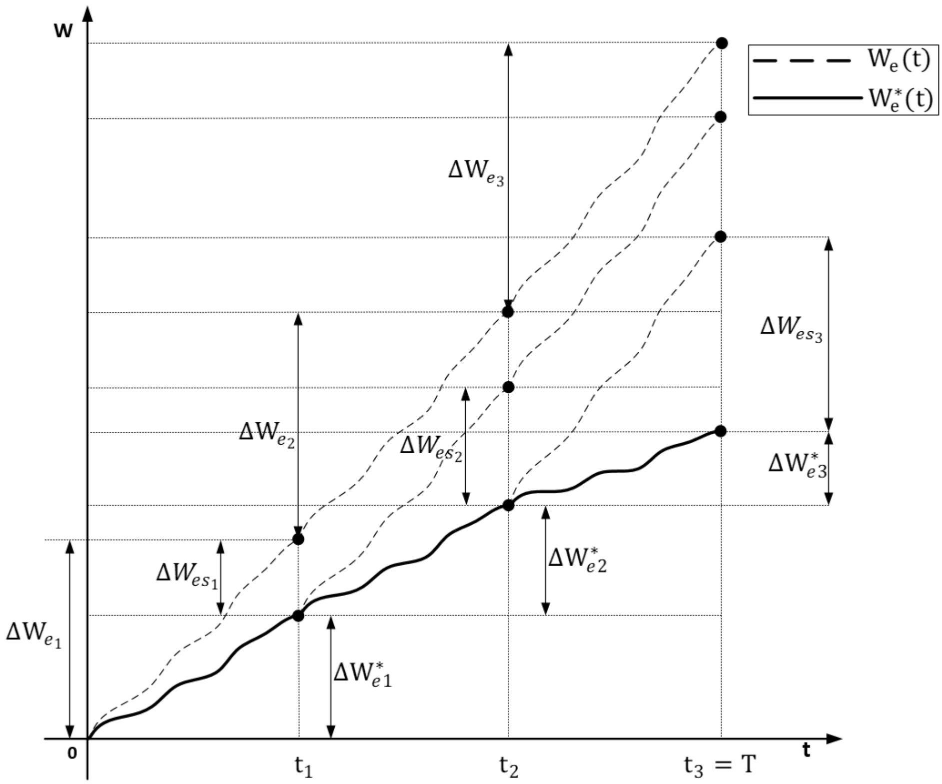

Figure 9: Time diagram for the illustration of the piecewise optimization algorithm. The continuous line represents the effective energy consumption, while the dashed lines represent energy consumptions assuming no piecewise optimization in the final sections of the route.

Fig. 10 illustrates the evolution of the piecewise optimization vector components along the driving cycle, while *Fig.11* shows the energy saving in each route section.

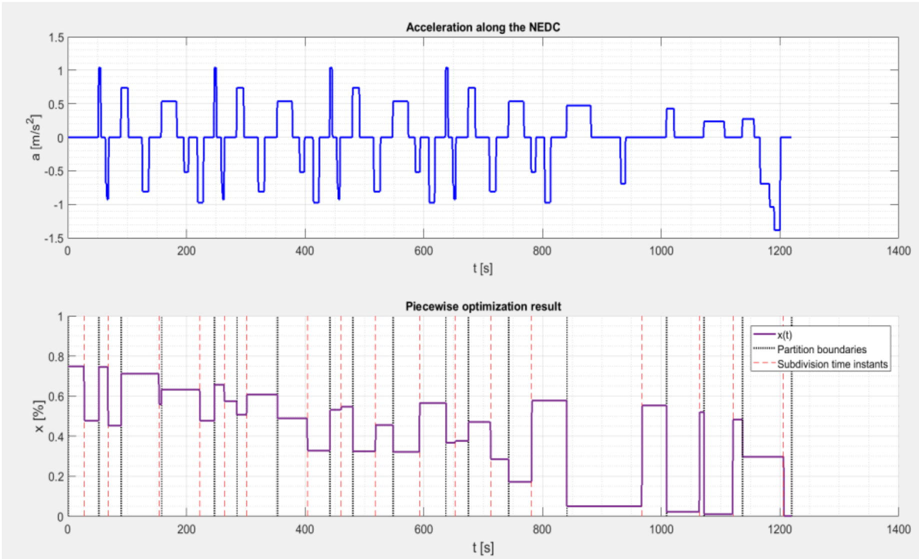

Figure 10: The NEDC acceleration profile (top), and the components of the piecewise optimization vector (bottom).

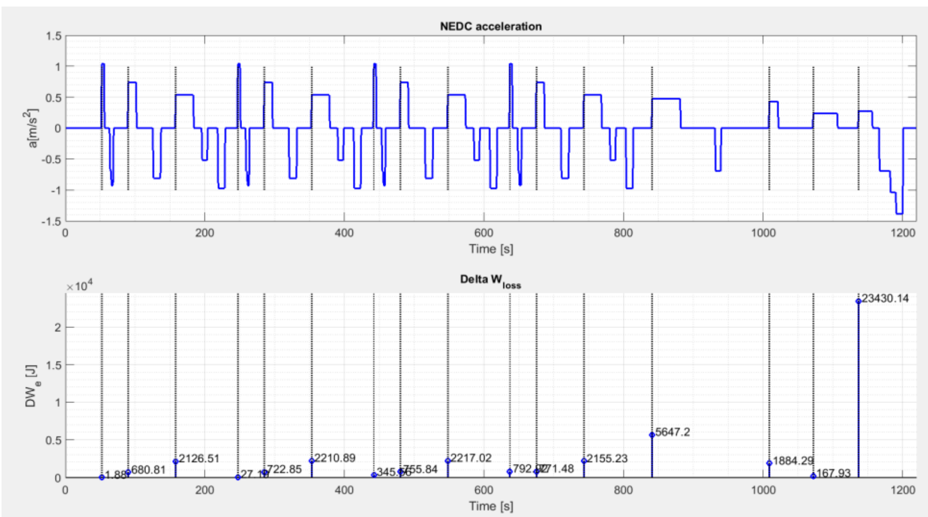

Figure 11: The NEDC acceleration profile (top) and the "electrical energy saving" along each route section (bottom).

The evolution of the battery state of charge (SOC) and of the supercapacitor state of energy (SOE) along the driving cycle is presented in *Fig. 12* for both the global and the piecewise optimization cases.

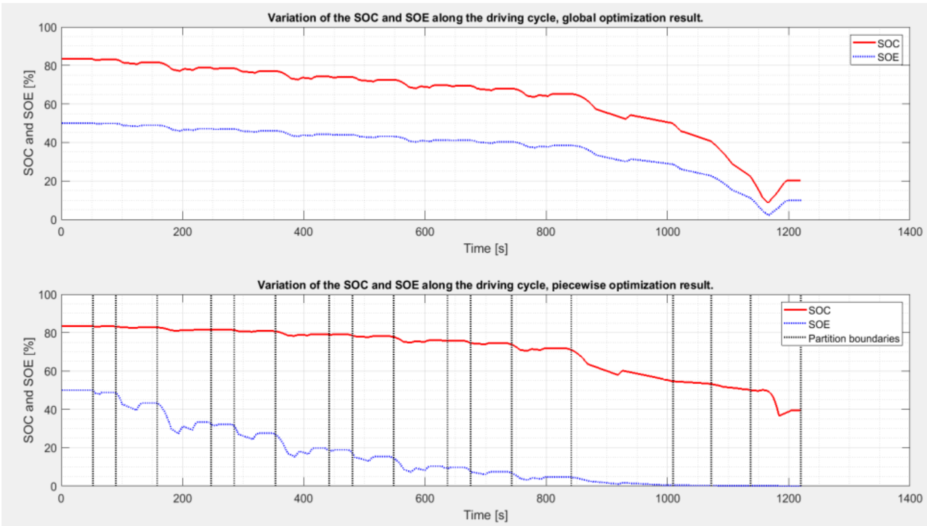

Figure 12: Variation along the driving cycle of the battery state of charge (SOC) and supercapacitor state of energy (SOE) in the global optimization (top) and piecewise optimization (bottom) cases.

Fig. 13 provides a proof of the improvement brought by the application of the piecewise optimization on top of the global optimization result.

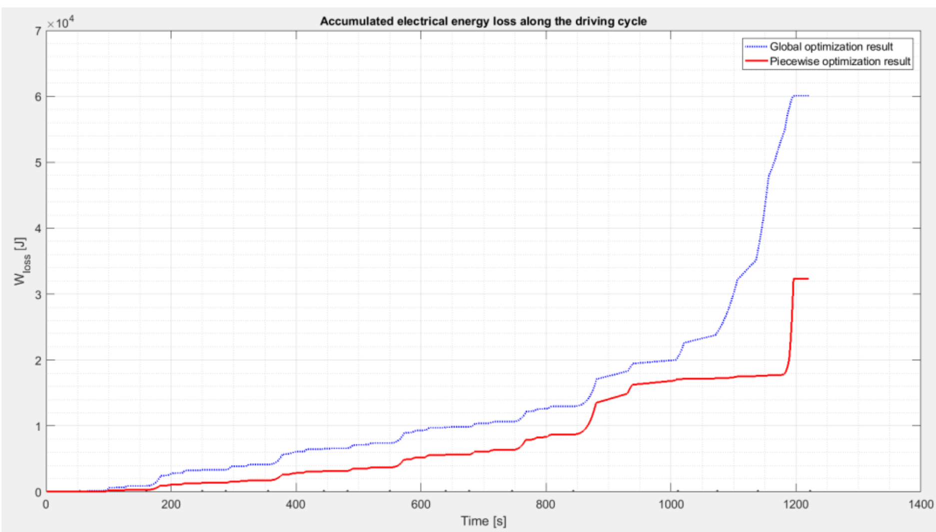

Figure 13: The accumulated electrical energy losses in the HESS along the driving cycle, in the global and piecewise optimization cases.

5. Conclusions

In the paper it has been shown that the energy loss minimization of a hybrid energy storage system over a standard driving cycle of an electric vehicle can be successful applying a low-dimensional optimization vector. The optimization has been performed in two steps: an iterative global optimization and a piecewise optimization of the partitioned route. In both cases the result of the stochastic search is improved step-by-step due to the knowledge gain about the energy requirement in previous optimization steps. Thus, a feed-back about the entire route yields the relaxation of the constraints and allows for better search results.

The detailed analysis of the driving cycle partitioning strategy remains a subject for future work.

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