Holistic Energy Management System for Battery Electric Vehicles using Sliding Window Optimization

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Abstract: This paper introduces an optimization based holistic energy management system for a battery electric vehicle. The energy management can adapt the velocity and the power consumed by the cabin heating, in order to minimize the energy consumption, while keeping total driving time and the cabin temperature within predefined limits. For the optimization a hybrid genetic algorithm is used. The approach is applied to a driving cycle, which is optimized by dividing it into separate time frames. This approach is referred to as sliding window approach. The results of the sliding window approach are compared to an optimization of the whole driving cycle. The results presented in this paper demonstrate the feasibility of the sliding window approach. Moreover, they show that the sliding window approach does not lead to a significant deterioration compared with the optimization of the whole driving cycle. At the same time the driver comfort remains well within the acceptable limits and the driving time constant.

Key Words: BEV, energy management system, multi-objective optimization, hybrid genetic algorithm

1. Introduction

The main disadvantage of battery electric vehicles (BEV) compared to conventional vehicles is their limited range. Moreover, electric vehicles tend to be more expensive and their lifetime is shorter. All these issues have a negative impact on the user acceptance. One possibility to address these drawbacks, is a holistic energy management system (EMS). The importance for such systems is rising for different reasons: Firstly, an EMS that allows a higher range for the vehicle, while also minimizing the component aging will decrease the total cost of ownership and increase the user acceptance. Secondly, the hardware in electric vehicles is becoming increasingly complex and diverse. As a consequence, more variables can and must be adapted within the vehicle. This in turn also leads to a more complex EMS. Lastly, the increase of computing power within vehicles means that increasingly complex strategies become feasible and can reasonably be used within cars.

This paper describes an optimization based EMS utilizing a genetic algorithm (GA). Currently, the system is implemented using a simulation model of the drive train as well as a simplified thermal model of the cabin. The simulation computes the parameters used to measure the performance of the vehicle. In this publication, the following parameters are computed: the energy consumption for a given route, the time required and the thermal comfort of the driver. These parameters must be quantified using objective functions f_i and can then be fed into a global fitness function $F(f_i)$. This means that an a priori multi-objective optimization is used and the individual weights for the fitness function are selected before the algorithm is run. The computed fitness value of $F(f_i)$ is used by the optimization algorithm to calculate optimized variable values for the next iteration. This procedure is repeated until a stop criterion is met.

This approach cannot be directly integrated into the vehicle for two reasons. The first reason is that in a real world scenario the future cannot be predicted exactly and, therefore, no global optimum can be determined. The second reason is that the computation power within the vehicle is limited, and the optimized variables must be available in real-time. In order to facilitate an easier integration into an existing vehicle, the so called sliding window approach is investigated. This means that the parameters are not optimized for the entire journey, but for the next section of the trip immediately ahead. For this purpose, perfect foresight is only needed for the next section.

The paper mainly contributes the following points:

- Practical example for the use of genetic algorithms for automotive applications
- Practical example for the potential of an optimization based holistic energy management
- Comparison between optimization of the whole journey and the sliding window approach

2. Related Work

In this section the literature on EMS for BEVs is briefly reviewed. It starts out with strategies that focus on individual components and continues with holistic strategies.

EMS for the auxiliary consumers are developed. The focus often lies on the Heating, Ventilation and Air Conditioning (HVAC) as it is the major auxiliary consumer. Strategies exist to split the power between traction and the auxiliary consumers optimally. The aim of these strategies is to shift the operating points toward the optimal operating range of the traction battery (1) (2).

Another aspect of EMS research is the thermal management within the vehicle. Approaches to this issue either focus on the thermal management of the drivetrain components or couple the components with the thermal management of the cabin (3) (4) (5).

Research also focuses on the use of two electric machines. An example for an EMS employing two machines can be found in (7).

Another emphasis lies on operation strategies that influence the velocity. If the route is predicted, an optimal velocity profile can be determined and the energy consumption can be reduced (8) (9) (10). Lu et al. (11) concentrate on a velocity profile optimized for a synchronous machine.

In (12) an architecture for a holistic EMS is introduced. This approach focuses on the overall architecture and not on the specific control strategy. Basler (13) also presents an approach for a holistic EMS for a BEV. Strategies usually employed by the EMS in combustion engine vehicles are examined and adapted for BEVs. The focus lies on agent-based strategies. The strategy itself is optimized using a multi-objective optimization. A similar agent-based approach is described by Meis (14), concentrating, however, on commercial vehicles containing more than one power source.

In (15) an on-line EMS based on Evolutionary Algorithms is proposed for a plug-in hybrid vehicle. They employ a sliding window approach in order to implement the system on-line, assuming perfect foresight for the next section of the trip.

3. Basics of Multi-Objective Optimization

In the following, the basics for multi-objective optimization relevant for this publication are introduced. The described equations are needed in Section 4.

Two different approaches to multi-objective optimization exist: a priori and a posteriori methods (16). The difference between the two approaches is at what point in time the decision maker must choose the desired point in the Pareto front. In an a priori method, the decision is made before the algorithm is run. For example, this can be done by devising a fitness function which weights the objective functions. When using an a posteriori method, the algorithm first comes up with the Pareto front, then the decision maker decides on one solution. In the following, only a priori methods are considered because they need a shorter computation time and come closer to a realistic application scenario.

In order to compare several objective functions f_i that contribute to a global optimization function $F(f_i)$, an approach based on the compromise optimization method is used (17). During optimization, the different objectives f_i are normalized within the range [0...1] by applying Equation (1). When an upper constraint is violated, i.e. the objective's result $\tilde{f}_i > 1$, a penalty, putting linear pressure on the fitness values, is applied in order for the individual to become feasible again (18)(19), see Equations (2) and (3):

$$\tilde{f}_i = \frac{f_i - f_{i,U}}{f_{i,N} - f_{i,U}} \tag{1}$$

$$\bar{f}_i = \tilde{f}_i + \langle \tilde{f}_i \rangle_{pen} \tag{2}$$

with the operator $\langle \cdot \rangle_{pen}$ being defined as

$$\langle \cdot \rangle_{pen} = \begin{cases} 0, \text{ if constraints fulfilled} \\ penalty(\tilde{f}_i), \text{ if constraints violated} \end{cases} \tag{3}$$

$f_{i,U}$ describe the Utopia-curves, i.e. the best possible curve or value the objective i can assume during a driving cycle. These can be calculated independently from each other (16). The worst physically possible values are called Nadir-points $f_{i,N}$. In this approach, the Nadir-values are set to objective function values obtained by applying a conventional controlling policy π of the BEV's variables, to force the used multi-objective optimization algorithm to find the global optimum. Finally, the $\bar{f}_i$ define the sum of the normalized objective values of a single objective function including, its penalties for violating a constraint.

The weighted sum method lets the decision maker assign their priorities $\boldsymbol{\theta} = (\theta_1 \ldots \theta_m)$ to the single objective functions f_i resulting in $F(f_i)$ described in Equation (4):

$$F(f_i) = \sum_{i=1}^{m} \theta_i \bar{f}_i \tag{4}$$

with $\sum_i^m \theta_i = 1$, where the index m denotes the number of objective functions f.

4. Approach

In this publication the optimization of driving cycles is considered. These represent well known test procedures and ensure the comparability of the results. In the following the results for the NEDC are presented.

For the chosen driving cycle the target velocity $v_{x,tar}(t)$ is transformed into $v_{x,tar}(x(t))$, so that velocity is expressed depending on the current position $x(t)$. Idle times $\Delta t_{n,idl}$ are extracted from the speed profiles $v_{x,tar}(t)$ and added during calculation of the fitness function's value $F(f_i)$ gained from simulation when an idle position $x(t)_{n,idl}$ according to the driving cycle is reached. Figure 1 depicts how the driving cycle is transformed from a representation of $v(t)$ to a $v(x(t))$. This combination of time and spatial dependency

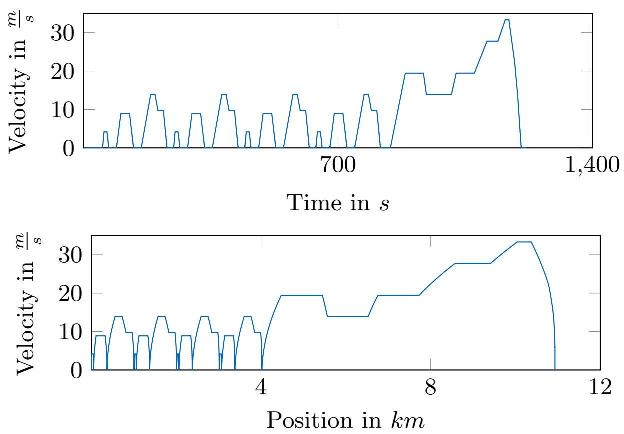

Figure 1: Top: $v_{x,tar}(t)$-curve, bottom: $v_{x,tar}(x(t))$-curve of the NEDC

makes the optimization of real-world trips feasible.

Using a hybrid GA, the goal is to minimize the deviation $\Delta T(t)$ from a desired cabin temperature $T_{des}(t)$ and the velocity deviation $\Delta v_x(x(t))$ compared with a target velocity $v_{x,tar}(x(t))$ derived from a standard driving cycle-trajectory $v_{x,tar}(t)$. Moreover, the accumulated energy demand $E(x(t),t)$ resulting from the vehicle's total power requirement $P_{cyc}(x(t),t)$ is minimized while keeping the optimized driving time Δt_{opt} similar to the original time Δt_{cyc}. In order to do that the power of the HVAC unit $P_{airCon}(t)$ can be varied from 0 to 5 kW and the vehicle's velocity $v_x(x(t))$ can be varied within the range of 10 % on a city road and 30 % on a highway compared with the baseline of the driving cycle. For each of the mentioned target values ($\Delta T(t)$, $\Delta v_x(x(t))$, $E(x(t),t)$ and Δt_{opt}), a single objective function f_i is defined according to Equations (5) - (9):

$$f_T = \frac{\int |T(t) - T_{des}(t)| dt}{\Delta t_{cyc}} \tag{5}$$

$$f_v = \frac{\int |v_x(x(t)) - v_{x,tar}(x(t))| dx}{\Delta x_{cyc}} \tag{6}$$

$$f_E = \int P_{cyc}(x(t),t) dt \tag{7}$$

$$f_t = \begin{cases} 0, & \Delta t_{opt} \leq \Delta t_{cyc} \\ \Delta t_{opt}, & \Delta t_{opt} > \Delta t_{cyc} \end{cases} \tag{8}$$

$$f_t' = \Delta t_{opt} \tag{9}$$

with Δt_{cyc} defining the simulated timespan of the driving cycle and Δt_{opt} being the time taken for the optimized speed profile to reach the destination. Δx_{cyc} is the accumulated driven distance. f_t describes a Mayer objective function that measures the value of Δt_{opt} at the end of the optimization, i.e. the last time step (20), and is normalized by Δt_{cyc}. The results of the objective functions f_i are obtained by assigning time series- and spatially discretized data to the BEV simulation, which is implemented to be run in parallel.

To ensure comparability among the single objective functions f_i these are normalized using Equations (1) to (3) discussed in Section 3 Finally, a single fitness function value $F(f_i)$ results by taking the decision maker's preferences $\boldsymbol{\theta}$ into account (Equation (4)). The result is a single optimized parameter set $\pi(x(t), t)$ instead of a Pareto front. At the end of the GA's optimization process, a local gradient-based solver is applied to the best variable-combination. As a result, overall calculation time is considerably reduced.

Parameter	Value
Population size	1.5·number of parameters to be optimized per section l
Number of max. generations	50
Crossover-fraction	0.80
Mutation rate	feasible adaption
Elitism	0.05·population size
Selection	rank based
Discretization step of time-dependent optimization parameters	5 s (?)
Discretization step of space-dependent optimization parameters	400 m

Table 1: Parameters of the GA

The strategy described above can be used to develop a global optimization policy $\pi(x(t), t)$ for the whole driving cycle. But it can also be adapted to the sliding window approach. For this the sliding window approach, the driving cycle is subdivided into sections $l = 1, ..., L$. Every section l is optimized separately with the same approach. A new section starts at each position where the vehicle stops. Consequently, an optimization policy $\pi_{l+1}(x(t), t)$ is only computed for the section $l+1$ immediately ahead. This shortened optimization horizon means that no global optimum for the whole test drive can be found. With the smaller prediction horizons the computation times are reduced. This approach is the first step towards the integration of the optimization based EMS into a vehicle, because it becomes feasible to optimize the driving cycle section $l+1$ ahead while traveling the distance of the current section l.

Configuration	Reduction of energy consumption	Time relative to original traveling time
Optimization of whole cycle		
$\boldsymbol{\theta} = (10\ 60\ 30)$	8.1 %	100 %
Original penalty function with sliding window approach		
$\boldsymbol{\theta}_1 = (20\ 50\ 30)$	0.825 %	100.0 %
$\boldsymbol{\theta}_2 = (10\ 60\ 30)$	1.34 %	99.9 %
Adapted penalty function with sliding window approach		
$\boldsymbol{\theta}_1 = (20\ 50\ 30')$	12.1 %	108.3 %
$\boldsymbol{\theta}_2 = (20\ 30\ 50')$	6.13 %	102.2 %
$\boldsymbol{\theta}_3 = (10\ 15\ 75')$	6.76 %	100.2 %

Table 2: Comparison of traveling time and energy consumption for different decision maker priority vectors $\boldsymbol{\theta}$

The GA is parametrized as shown in Table 1. The population size is adapted to the number of parameters that are optimized per section l. The total distance in x and the driving time per window l determine the number of parameters to be optimized.

5. Results

In this paper only the results of the sliding window approach are presented, as the results for global optimization can be found in a previous publication (?). The results using the sliding window approach are compared with the results when optimizing the whole cycle.

For all experiments, the temperature of the environment was set to $T_{env} = 10\ °C$ and the desired cabin temperature to $T_{des} = 22\ °C$. The vehicle is preconditioned to $T_{start} = 18\ °C$. Figure 2 shows the energy consumption and the temperature deviation for the sliding window approach. The left hand part of the figure displays the results with two different decision maker priority vectors $\boldsymbol{\theta}$. The final seconds of the driving cycle are enlarged in the figure. This allows the reader to compare the arrival times. $\boldsymbol{\theta}_1$ weighs the temperature deviation ΔT_{cab} with 20 %, the energy consumption E with 50 % and the journey time Δt_{opt} with 30 %. As described in the approach, the weighing of the journey time Δt_{opt} is realized as a Mayer objective function f_t. The second priority vector $\boldsymbol{\theta}_2$ weighs the temperature deviation values ΔT_{cab} with 10 %, the energy consumption E with 60 % and the journey time Δt_{opt} remains at 30 %. The figure shows that for the different priority vectors $\boldsymbol{\theta}_{1/2}$ the result is a different point on the Pareto front. However, both configurations allow for a comparatively small reduction in the energy consumption E of about 1 %. Table 2 summarizes the results for the different priority vectors. The reduction in the energy consumption E and the traveling time Δt_{opt} relative to the original time Δt_{cyc} are summarized. Previous results for the optimization of the whole driving cycle show a significantly higher reduction in the energy consumption E using the same priorities $\boldsymbol{\theta}$ (**?**). One reason for this is, that the smaller optimization and prediction horizons in the sliding window approach allow the vehicle's velocity $v_{x,tar,opt}(x(t))$ as well as the HVAC's power $P_{airCon}(t)$ to be adapted only within the smaller range in a window l. For every window l the driving time Δt_{opt} must not exceed the original one in the base scenario without optimization. One way to address this, is to change the way of weighing the driving time Δt_{opt}. Instead of the penalty function f_t, the driving time Δt_{opt} is now weighted in the same way as the other parameters using the objective function f'_t. Thereby, the algorithm aims to keep the driving time Δt_{opt} for every window l as short as possible as a differentiation between driving times Δt_{opt} that are equal to or smaller than the original driving time Δt_{cyc} are realizable.

The right hand part of Figure 2 shows the results obtained by the adapted optimization using f'_t instead of f_t. This time, three different decision maker priority vectors ($\boldsymbol{\theta}_1$, $\boldsymbol{\theta}_2$, $\boldsymbol{\theta}_3$) are depicted. It is evident that the driving time is weighted higher in this scenario. For $\boldsymbol{\theta}_3$ the driving time in f_t is weighted with 30 % to compare the effect of the new objective function f'_t with the old one f_t. In this case, the overall traveling time is 108.3 % of the original one Δt_{cyc}. Consequently, the effect will be noticable for the driver. This is considered to be not acceptable. Therefore, a different area of the Pareto front is investigated. When weighing f'_t with 75 %, the traveling time Δt_{opt} is 100.2 % of the original driving time Δt_{cyc}. Simultaneously, the energy consumption E can be reduced by 6.76 % while keeping the driver's comfort well within acceptable limits.

From the results it can be deduced that the sliding window approach works well in combination with the hybrid genetic algorithm for a driving cycle. The approach that has been developed for the optimization of the whole driving cycle can be applied to the optimization with the sliding window approach. However, in order to obtain satisfactory results the approach had to be adapted. With this adaption the results are very similar to the ones gained with the optimization of the whole cycle (**?**).

6. Conclusion

This paper describes a holistic optimization based EMS. The implementation using a hybrid GA and a sliding window approach is described in detail. The proposed method is applied to a standard driving cycle namely the NEDC. Thus its feasibility could be demonstrated. Additionally, the paper compares an optimization of the whole driving cycle with the sliding window optimization. It can be shown that the section wise optimization does not lead to significantly inferior results, if the weights of the objective functions are adapted and no Mayer penalty function is used. The results demonstrate the overall feasibility and mark the direction for future work.

Future work will concentrate on the expansion of the presented approach. The main focus will lie on developing an EMS that can be used on-line in the vehicle. For this purpose the sliding window approach will be expanded in order to work with an inaccurate forecast. This means that in addition to the optimization of the next time frame a control system is used, which adapts the strategy to the aberration from the prediction.

Moreover, future experiments with recorded data from real-world test drives will be conducted.

7. Contributions

As the first author K.M. developed the overall concept for the described EM and supervised the master's thesis of T.H. T.H. drew up the simulation described in the approach and generated the results used in this publication. M.S. assisted in the overall reviewing process of the paper and in the writing process. M.L. made an essential contribution to the conception of the research project. He revised the paper critically for important intellectual content. M.L. gave final approval of the version to be published and agrees to all aspects of the work. As a guarantor, he accepts responsibility for the overall integrity of the paper.

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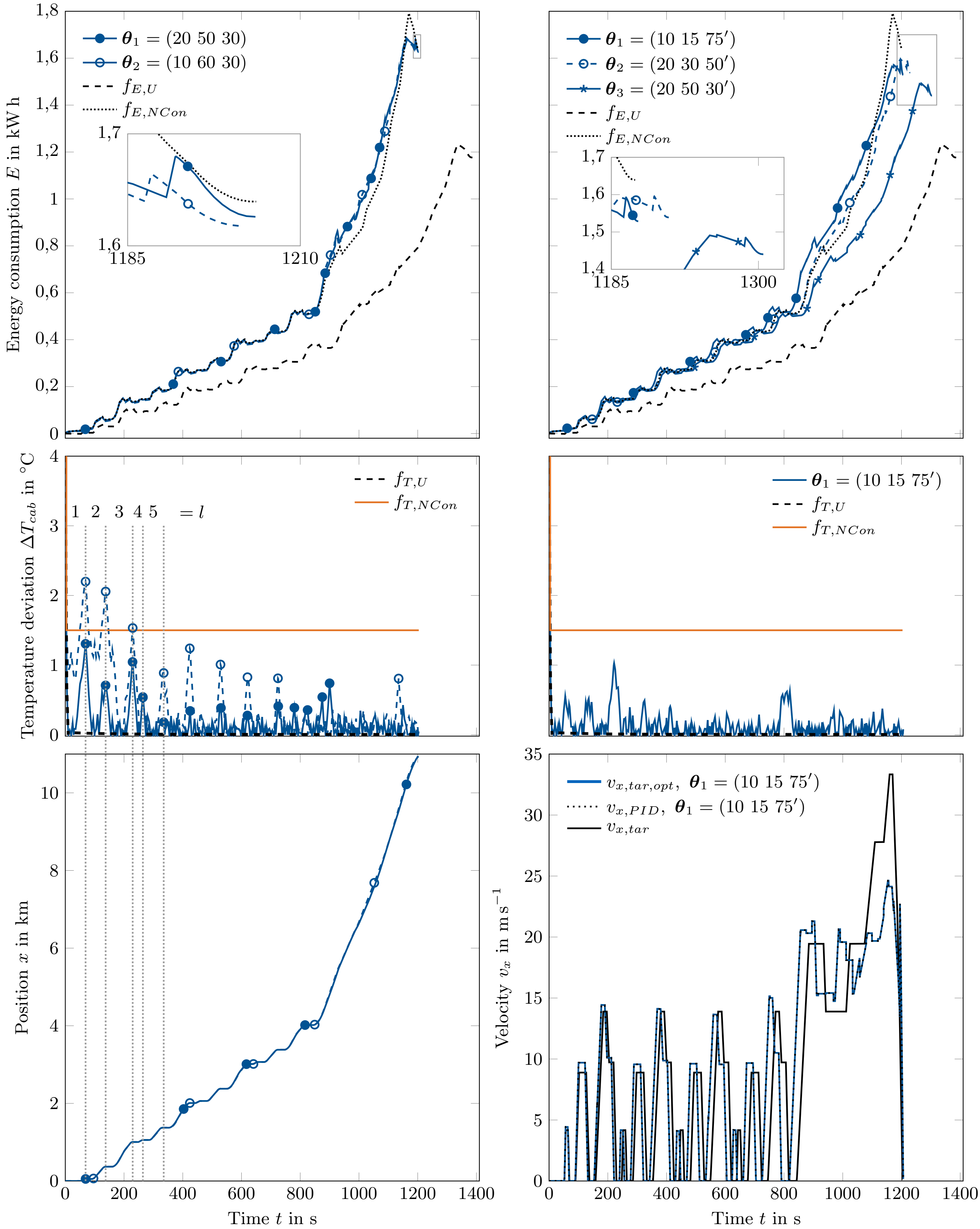

Figure 2: Sliding window approach with same decision maker priority vectors $\boldsymbol{\theta}_{1/2}$ as in the optimization of an entire driving cycle (left); sliding window approach with the decision maker priority vectors $\boldsymbol{\theta}_{1/2/3}$ using f_t' instead of f_t (right)

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