Battery & Energy Management by Real-Time Model-based Optimisations
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ABSTRACT

Digital Models for Mechanics, Power Train, Power Sources, Generators, Converters and Electrical Consumers are today developed and used in a large extend, for simulation and validation in different industrial domains. In Automotive applications, the increasing use of electronics and electrical modules lead to a more and more complex on-board powertrain & power-net in a serial production car.

In that context, for a better durability and cost reduction, main problems to face are: engine & powertrain optimization, battery sizing, miss-discharge preservation, diagnosis of electric components, consumption optimization, and more generally on energy management. For this purpose, models are helpful used for preliminary off-line analysis and optimization. But in standard automotive on-board controllers, only pre-defined (mapped) outputs are implemented, mainly because of real-time constraints of serial µ-controllers and lack of adequate algorithms development.

The real-time optimization described in this paper is applied to Battery Management Systems and to Vehicle Energy Management Systems, based on internal models of battery and of electrical consumers. The optimization strategy depends on the driver request, on the external driving conditions, on the current running point efficiency of the powertrain (combustion engine, electrical motor with or without automated transmission), and on the electrical status (battery state of charge, alternator efficiency, electrical consumers characteristics). For this purpose, a new approach is described in this paper, using model-based algorithms. The optimization is on-line computerized with fast ‘internal simulation’ of the global system. Kind of recursive algorithms can then provide the optimal solutions at each sample time.

Main advantages of the model-based optimization are: a better performance (results are tested at each sample time), a better robustness to deviations (the internal models can be auto-adapted), and a better flexibility and maintainability, since any modification of any component of the global vehicle system can be simply translated in modifications of the internal models. Thus, the optimization algorithms themselves are not modified, and any long re-tuning is no more necessary.

The direct application concerns a more robust battery diagnosis and electrical power-net control, for energy use optimization. Some simulation and real tests are described, which provide promising results, able to improve significantly the energy use in a vehicle.

Applications are wide open: for automotive powertrain & power-net management as described here, as well as for many other industrial applications, as aerospace electrical control, building lighting, handy phones, etc…

INTRODUCTION

Internal Models for Mechanics, Power-Train, Power Sources, Generators, Converters and Electrical Consumers are today developed and used in a large extend, for simulation and validation in different industrial domains. In Automotive applications, the
increasing use of electronics and electrical modules lead to more and more complex on-board power-train & power-net controllers in serial production cars.

In that context, for a better durability and cost reduction, main problems to face are: engine & power-train optimization, battery sizing, miss-discharge preservation, diagnosis of electric components, consumption optimization, and more generally energy management.

For this purpose, models are helpful for preliminary off-line analysis and optimization. But in standard automotive on-board controllers, only pre-defined (mapped) outputs are integrated and implemented, mainly because of real-time constraints in serial µ-controllers and of lack of adequate algorithms development for a more efficient integration.

The real-time optimization strategy of the on-board combustion & electrical energy consumption proposed in this paper is based on automatic real-time up-dated decisions applied to: gear-shifts, torque delivery, and battery charge. This strategy depends on the driver request, on the external driving conditions, on the current running point efficiency of the power-train (combustion engine, electrical motor with or without automated transmission), and on the electrical status (battery state of charge, alternator efficiency, electrical consumers characteristics). For this purpose, a new approach is described, using model-based algorithms. The optimization is on-line computerized from fast ‘internal simulations’ of the global system. Kind of recursive algorithms can then provide the optimal solutions at each sample time.

Three strategies are described:
- a ‘local’ or ‘static’ optimization, centered on the current running point,
- a ‘global’ optimization related to the whole trip planning (in case of profile information available from a navigation system),
- and a ‘predicted’ optimization on a ‘moving-time-window’ defined as the near next time period of few seconds, including all the predictable large-scale, high and low-frequency dynamics of the whole system (power-train + electrical power-net), modeled and integrated into the on-board micro-controllers.

Main advantages of the model-based optimization are: a better performance (results are tested at each sample time), a better robustness to deviations (the internal models can be auto-adapted), and a better flexibility and maintainability, since any modification of any component of the global vehicle system can be simply translated in modifications of the internal models. Thus, the optimization algorithms are not modified, and any long re-tuning is no more necessary.

Two main applications are described in this paper:
1) an optimal management of engine torque and transmission gear-shifts,
2) and a more robust battery diagnosis for optimization of the electrical energy use.

Some simulations and real tests are described, which provide promising results, able to improve significantly the energy management of a vehicle.

**GENERAL APPROACH**

**Model-based Optimization**

Any physical process can be modelled and represented by the inputs-to-outputs relations identified inside the process. To control this process means to find an inverted representation of the process itself, so as to detect the appropriate inputs able to control the outputs according to the required objectives. In case of lack of sensors, which is the case of the automotive applications considered in this paper (no direct measure of torque or of electrical capacity), the control has to be based on the internal model available from expertise and experiments.

A direct inverse of the process, i.e. an outputs-to-inputs model, can be defined and used in open-loop architecture, as shown in the following figure:

![The typical open-loop Control Diagram](image-url)

The calculations of the inverted model parameters are to be made with off-line procedures, tuned on tests benches, and usually built from large maps which must include the whole functional domain to be controlled, and which inversion is not systematic. In that case, for complex systems as automotive power-trains (dedicated to the control of mechanical torque), or secondary batteries (dedicated to the control of electrical state-of-charge), the models can be really difficult to inverse, or the performance will suffer unavoidable instabilities, dispersions or deviations due to the open-loop structure.

In power-train controls, the torque generation from internal combustion engines and its conversion through the mechanical transmission have to be represented in multi-dimensional maps, with high order-dynamics.

In electrical energy control, the state-of-charge indicator is extracted from strongly non-linear representations of the battery behaviour, also with high order-dynamics.

Both physical process models are difficult to invert, as mentioned further in this paper. So, another solution is advantageously proposed, based on an internal model closed-loop structure, where the Direct Model without any inversion is implemented so as to make iterative operations to get the appropriate inputs required to the process, as shown in the following figure:
This structure is adequate for sensors-less process control, and has some advantages, as:
- the model is not inverted, so there is no need for preliminary off-lines calculations;
- the initial accuracy of the direct model is preserved;
- the closed-loop control strategy allows to define and select the control dynamics, for example damping effects.

For sensor feedback processes, any evolution of the process to be controlled can be adapted and easily introduced in the direct Model; the global control strategy remains valid, associated to a parallel auto-adaptive control, as shown below:

Three modes of optimal control are considered thus:

1. a ‘local’ mode, defined as an optimization of an instantaneous criterion, taken at the present current time; this solution requires less computer resources, and provides the instantaneous optimal solution of the current running point;
2. a ‘global’ mode, defined as an optimization of criterion on a complete timed scenario, typically on a planned trip (fixed, minutes or hours long); this solution requires then more computer resources –but now more available on recent calculators-, and provides a ‘supposed to be global’ optimal solution for the whole trip period (related to the navigation system in automotive applications);
3. an ‘intermediate’ mode, based on a “moving-time-window” defined as a ‘next-future’ prediction (variable, few seconds or minutes); this can be a compromise between the ‘local’ and the ‘global’ solutions, with possible better efficiency with limited resources for calculation. Note that in that case the prediction window is variable, with a possible high jitter.

The selection of the “moving time-window” in which some prediction of the next future is made, depends on the application.

Let’s consider few examples:
- the next gear shift phase (few seconds duration): if activated, this mechanical operation implies some additional energy consumption, so the criterion must take it into account;
- the next change of present driving conditions, from city to highway (few minutes duration): the external constraints can change and imply different use of electrical energy use;
- the next activation or de-activation of equipments onboard, air-conditioning, or seat heating (few seconds or minutes): the demand of energy can then be predicted and introduced in the optimization process.

The predictions are made by ‘fast’ internal simulations, i.e. some iterative computations of the model outputs, from the pre-defined future inputs and constraints, on the horizon considered.

Variable-scale Prediction

This model-based approach makes also predictions possible, from pre-defined inputs scenarios. This technique is inspired from the well-known predictive control approach, which gives substantial positive advantages and is appropriate for delayed processes, as described in references (1) and (2).

The solution proposed in this paper is thus based on such predicted-, auto-adaptive model-based control, applied to automotive applications as described in following chapters.
The critical point is to select pertinent future windows of prediction, not too short to include useful informations, not too long to limit the CPU load impact.

Real-time Implementation

Considering the possible increase of the CPU load due to such long iterative calculations, the actual impressive improvement of performances in new on-board electronic calculators makes this type of solution really available today and efficient for series production, as a promising solution for next tomorrow.

The implementation of these algorithms requires some specific software structures, as pre-emptive iterations for solving the optimization objective, defined as:

```
for i=1 to N, until error < requested precision
```

activated until a solution is reached (or a maximum of N iterations are operated)

These algorithms are dedicated to back-ground tasks, were the whole process is made until an acceptable solution is reached. This process can be interrupted of course, and is basically different from the usual sampled tasks running at a constant rate.

Another specific software structure is introduced by the internal closed-loop process, from model to observer, and vice-versa, defined as:

- "outputs = Model
  (from present inputs and internal states) ;"
- "new parameters of Model = Observer
  (from model outputs and measures) ;"

activated with a constant sampling time recurrence.

Such sequential modules are to be taken in a fixed order, so as to assume that the output feed-back is coherent, whatever could be the time of calculation.

Real-Time schedulers have today to accept such software structure and constraints. The control signals process become then the result of real-time on-board solving processes, which replaces the former open-loop solutions using pre-calculated off-line tables or maps.

AUTOMOTIVE POWER-TRAIN OPTIMIZATION

As a first illustration, let’s consider a hybrid vehicle (see (4)), defined as follows:

This is a typical parallel hybrid car, where the torque provided at the clutch is the direct sum of the torques from the internal combustion engine (ICE) and from the electrical starter-generator (SG) – also called starter-alternator. In this car, the SG is integrated, i.e. put on the same crank-shaft axis. A variant can be a “Side Starter-Generator”, connected by a belt transmission, parallel to the main axis, not used here.

The transmission gear box is an automated manual transmission (AMT), which provides either a manual-sequential mode, or a full-automatic mode.

The SG is connected to a 42V electrical power-net (high voltage needed, compatible to the adequate 4kW nominal power), connected to a 36V-42V battery.

An additional 12V battery is used for the standard electrical equipments supply, via a DC/DC converter. This battery is assumed to be in constant charge, and doesn’t participate in the energy management for simplification reasons.

The driver pedal indicates the driver request, considered as a ‘power’ request, as the driver wishes a vehicle acceleration.

Control domain of Hybrid Vehicles

Such power-train configurations lead to consider at least 4 main parameters to be optimized:

- the torque at the clutch, which is constraint to track the driver request;
- the torque distribution between ICE (fuel or diesel) and the SG (electrical reversible motor, in charging mode or in generator mode);
- the gear ratio of the transmission (automated or not);
- the SOC State-of-Charge of the Battery, to be preserved.

The criteria to optimized are based on the fuel consumption (to minimize), the efficiency (to maximize), and the global SOC variation (to minimize on a timed trip, or to constraint to recover the initial SOC at the end of the trip).

The Torque distribution becomes an additional degree of freedom of the system, as described in (5), and the required torque at the clutch can be supplied from diverse combinations of torque from the ICE and torque from the SG (the latter being reversible, in motor or generator mode).

The gear ratio is an important parameter, since the efficiency of the transmission depends on it. In case of an automatic transmission, the gear is automatically selected and shifted to the ‘optimal gear’. In case of a manual transmission, the ‘optimal gear’ can be displayed to the driver, when necessary, as a recommended ratio.

The SOC becomes an additional parameter (compared to standard vehicles where the battery doesn’t
participate to the torque generation), and requires an
efficient prediction of the use of electrical energy,
alternating boost phases and recovering phases, so as
to limit de variations, aiming a target of an iso-SOC at
the beginning and at the end of the trip.

This optimal torque control is built from an internal
model of the power-train torque generation, in closed-
loop with a permanent iterative calculation of the
optimal solution, according to the fuel consumption
criteria.

The following picture shows the domain explored for the
‘local’ optimization (at the present instant), where the
optimal solution has to be searched and detected.

![Domain of Optimization of a parallel hybrid
power-train](image)

**Figure:** Domain of Optimization of a parallel hybrid
power-train

The instantaneous (‘local”) criterion to minimize is then
the specific fuel consumption of the ICE, which is
extracted from this torque-vs-speed map representation,
according to the driver power request. The following
figure shows an example of this local optimization,
where the specific fuel consumption lines tend to select
the highest ICE torque at the minimal speed, for the
lowest gear ratio selection available. The torque surplus
can be then used as energy for recharging the battery
via the SG, according to the present SOC of the battery.

![Local optimization of the specific fuel
consumption, detected on a 3rd gear selection.](image)

**Figure:** Local optimization of the specific fuel
consumption, detected on a 3rd gear selection.

**Prediction capabilities**

This local optimization can be advantageously
completed by some predictions on future periods. The
interest of additional predictions is pointed out as the
possibility to include the energy impacts of future pre-
defined phases, as gear shifts or boosted accelerations
(for short-term periods), or to take into account specific
driving conditions, as urban, extra-urban, or highway,
which can run on mid- or long-term periods.

Considering a standard EUDC cycle, and some variants
from it, we propose to calculate the global optimal
control scenario, to check the minimal fuel consumption
available on this pre-defined speed profile. This global
optimization is made by typical non-linear dynamic
optimization algorithms (as mentioned in (3)), based on
backward iterations, to provide the optimal torque and
the optimal gear ratio to be applied during the whole
cycle, considering the fuel global consumption and the
battery state-of-charge variations.

As a first result, we can observe the optimal gear ratio in
the following figure:

![Global optimal gear ratio (green line), compared
to manual pre-defined set-points (red line).](image)

**Figure:** Global optimal gear ratio (green line), compared
to manual pre-defined set-points (red line).

The optimal gear ratio does not differ very much from
the normalized set-points pre-defined in the standard
EUDC cycle for manual transmissions. This optimal
solution proposes the same ratios during transients,
and a higher ratio on steady speeds, to get lower fuel
consumption. This can be modulated when introducing a
“torque reserve” strategy, which implies lower gear
ratios so as to preserve some potential fast acceleration,
leading to a complete similar scenario as the standard
manual one.

An interesting point is that this ‘global’ optimal solution
for gear ratio control is similar to the solution provided
by the ‘local’ optimization strategy. That means that it is
not worth predicting any future scenario to get the
correct optimal gear ratio (it doesn’t depend on long-
term predictions). The optimal strategy can be then
simplified for the gear ratio decision.

The following figures show the battery SOC behaviour,
optimized on variants cycles, where the extra-urban
phase is moved or duplicated, from its initial definition
located at the end of the EUDC cycle.

![Battery SOC control, on different variant cycles.](image)

**Figure:** Battery SOC control, on different variant cycles.
The ‘global’ optimization makes the use of the Battery correctly depending from the extra-urban phases where a high-efficient charge is available.

Also depending on the engine temperature, cold cranking conditions (blue line) imply a deeper discharge of the battery, than in hot cranking conditions (red line).

On an exclusive urban cycle (green line), the battery is less used because the recharge is more difficult without any high speed phase.

When considering the ‘moving-window’ prediction strategy, different simulations show clearly that the useful future horizon for the better prediction can be limited to certain phases, characterized on the external driving conditions: urban, extra-urban, highway, mountain…

Based on this classification, we can introduce specific strategies and criteria, so as to manage the ICE, the SG and the Battery to optimize the global energy consumption. Those strategies are to be defined in the general way as described in the following examples:

- For long city phases: the battery discharge is limited;
- For long highway phases: the battery can be punctually used for torque assistance or boost, and efficiently recharged;
- For city phases followed by highway phases: the battery can be discharged deeper during city phases (for fast cranking, stop-on-idle, boost…) since it can be efficiently recharged during highway phases.
- For mountain phases: the battery is used for boost until a limited discharge level. The driver should be informed or alerted in that case on the real limited battery capabilities status.

The different strategies define either a constant SOC reference set-point, or a variable SOC reference set-point. Additionally to that, a configuration using Double-Layers Capacitors (DLC super capacitors) has been tested, where the SOC variations are much more dynamic that with a secondary battery.

Real tests on EUDC and Japanese cycles made with the Siemens “SuperCar” demo-car, controlled by a predictive power-train strategy show promising results, as shown below:

<table>
<thead>
<tr>
<th>performed test</th>
<th>fuel consumption (l/100km)</th>
<th>fuel savings</th>
</tr>
</thead>
<tbody>
<tr>
<td>reference EUDC</td>
<td>8.527</td>
<td>-</td>
</tr>
<tr>
<td>reference JAP_1015</td>
<td>8.369</td>
<td>-</td>
</tr>
<tr>
<td>EUDC battery SOC ref constant</td>
<td>7.940</td>
<td>-6.88%</td>
</tr>
<tr>
<td>JAP_1015 battery SOC ref constant</td>
<td>7.266</td>
<td>-13.2%</td>
</tr>
<tr>
<td>EUDC battery SOC ref variable</td>
<td>8.254</td>
<td>-3.20%</td>
</tr>
<tr>
<td>JAP_1015 battery SOC ref variable</td>
<td>7.211</td>
<td>-13.8%</td>
</tr>
<tr>
<td>EUDC DLC</td>
<td>7.821</td>
<td>-8.28%</td>
</tr>
<tr>
<td>JAP_1015 DLC</td>
<td>7.367</td>
<td>-12.0%</td>
</tr>
</tbody>
</table>

Results are good on the EUDC cycle, from -3% to -8% of fuel reduction –relative to standard vehicle performances-, depending on the prediction strategy. This is due to the fact that the cycle is based on 2 different phases clearly separable (urban, and extra-urban), allowing an efficient SOC management, with distributed discharges and re-charges.

Results are better on the Japanese cycle, from 12% to 13% of fuel reduction, based on only urban driving conditions where the impact of stop-on-idle is higher, with hot initial cranking conditions.

Using DLC provides the best results on EUDC, since the ability for discharge and for charge acceptance is higher than with standard batteries.

**BATTERY DIAGNOSIS**

The battery becomes obviously a critical component in the energy management systems for hybrid power-train vehicles, as indicated above. It is now generally admitted to make strong efforts for battery diagnosis system developments, able to detect the real state of charge and state of health of the on-board battery (or ‘batteries’, since some vehicles can be equipped with dual batteries).

Considering the battery behaviour, predictions are required to avoid typical break-downs at crank, so the state observation must be made for relatively long-term periods (some days…). This leads to introduce a pertinent model-based approach, used in an optimization algorithm controller so as to extract the more efficient energy from the battery. As previously described, this optimization can be made by internal closed-loop iterations, where the battery outputs are predicted, and some criteria are to be optimized.

**Modelling aspects**

Modelling the battery is not easy, because of the high complexity of all the different electro-chemical phenomena involved in. We will not develop the modelling details, but it appears that a “just complex enough” model is available and adequate to predict the battery behaviour with accuracy enough for the global optimization targets.

The SOC accuracy commonly available is around +/-10%, which remains coherent with the limits for the depth of discharge to be checked, at around 60%. The impact of this precision on the state of health remains negligible in that purpose, or can be considered as negligible, in the sense that a compromise is supposed to be achieved between precision and complexity.

**State-of-Function approach**

As commonly agreed now by all Automotive Industrial applications actors, the State-Of-Function SOF becomes the explicit target of any energy-management
strategy. The SOF is defined as the capability of the on-board system (power-train + battery) to perform a predefined scenario. That implies directly a prediction of the system behaviour, considering the present situation, the constraints, and the targets to fulfill.

A similar structure is then proposed, so-called “observer” technique, applied to the battery component, based on an internal closed-loop of the modelled outputs, which can be simulated on the predicted desired scenario, as shown in the following figure.

The stability of such algorithms is preserved, since the Model is intrinsically stable, and the closed-loop feedback is tuned at a frequency, out of the Model bandwidth, whatever can be the disturbances on the direct inputs measurements.

The typical battery SOC can be predicted on middle-term horizons, where the integration of the current has low influence on the final SOC accuracy.

For long-term predictions, the system is not able to reach the required accuracy. But since an ‘intermediary’ optimization of the energy consumption can be made, using separated phases related to the external driving conditions, the battery SOC is then not worth being predicted on long horizons. The internal SOC model accuracy remains then sufficient for the energy optimization purpose.

Considering the State-Of-Health SOH indicator, this is observed in real-time, by the means of measurements of certain internal characteristic parameters of the battery, such as internal impedance, maximum capacity, dynamic polarization, or charge acceptance. Damages can be sudden or unexpected, so a constant observation is required.

On the other hand, a kind of prediction is possible, based on the time of use of the battery, correlated to its “age”. The history of cycles endured by the battery can also integrate some predictable ageing effects.

Typical SOF have been tested, as the crank-ability, obtained from the model-based prediction of the available power to be extracted at next cranking, checked relatively to the minimum required power. Some results on real tests are shown in the following picture:

The predicted power rate (yellow line on the bottom) is compared to a minimum threshold, for the crankability detection (as “yes” or “no”).

The predicted power rate (pink line) is defined in % and can be used as a relative SOF indicator of the present crankability function.

CONCLUSIONS

We propose in this paper a general discussion on the use of model-based algorithms, able to provide predictable behaviour of the physical process to control. The internal models are defined in a “just complex enough” representation, so as to be integrated in series controllers typically used in automotive applications.

These models can be used efficiently in real-time optimization algorithms, designed to provide the optimal control solution, considering the present states values, constraints and targets to achieve. Three optimization modes are described: the ‘local’ optimization provides an instantaneous solution, the ‘global’ optimization needs a prediction on a whole scenario (typically a planned trip), and an ‘intermediary’ optimization based on limited horizons appear as a good compromise providing pertinent predictions from reduced calculations load.

These algorithms are mainly based on iterative calculations which can be implemented as possible ‘back-ground tasks’, compatible with the real-time constraints.

Two applications on the automotive area are described, based on such techniques:

- an optimal torque control of hybrid power-train vehicles show substantial improvements, using the ‘local’ optimization for optimal gear shifts, and the ‘global’ optimization for the battery SOC preservation; efficient solutions can be obtained with an ‘intermediary’ optimisation strategy applied on limited phases to the SOC control.
- an optimal battery control and diagnostic is proposed on a similar model-based ‘observer’ approach, where
the predicted states are used to detect the capability of the battery to perform pre-defined scenarios, defined as State-Of-Function SOF targets.

The field of applications of real-time optimal control strategies can be extended to wide open systems: to automotive power-train & battery management as described here, as well as to many other industrial applications, as aerospace electrical control, building lighting, handy phones, etc…

REFERENCES


