Predictive Control for Energy Management in All/More Electric Vehicles With Multiple Energy Storage Units

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Keywords

Automotive applications, DC power supplies, Efficiency, Electric vehicles, Energy system management.

Abstract

The paper describes the application of Model Predictive Control (MPC) methodologies to a laboratory based electric vehicle traction system incorporating a super-capacitor peak power buffer, valve-regulated sealed lead-acid traction battery, high efficiency permanent magnet traction machine, and power conversion electronics. Particular emphasis is given to the co-ordinated management of energy flow from the multiple on-board power/energy sources to address issues of extended vehicle range and battery life-time for electric vehicle drive-trains, whilst accommodating operational constraints and, ultimately, generic non-standard driving cycles. The paper considers the case of an all –electric drive-train however, the techniques are also applicable to hybrid or more-electric drive-train topologies.

Introduction

The drive towards the development and realisation of environmentally friendly vehicles is resulting in the adoption of new power train formats, augmenting the more traditional internal combustion engine (ICE) with electrical torque assist [1], or with multiple electrical energy/power sources [2]. Although significant advances are occurring in battery and fuel-cell technologies to improve their energy density and cyclic efficiency/lifetime, due to their limited specific power capability, alternative peak-power buffer technologies, i.e. super-capacitors and high-speed flywheels, are being developed for incorporation into vehicle drive-trains. Primary objectives are, therefore, to improve both the vehicle range and battery cycle life through optimal management of the on-board power and energy, and realise full utilisation of the installed storage capacities. However, with the increasing complexity of power train formats, there is a requirement for more advanced control strategies to extract maximum benefit from each energy source. Here, the paper discusses the application of predictive control techniques for enhancing battery life-time and vehicle range, to an all-electric urban vehicle, although the principles are equally applicable to hybrid vehicle configurations.

Methodologies currently employed for energy management are generally the result of extensive experimental trials and iterative modifications, resulting in map-based empirical solutions that possess limited flexibility to cope with different driving styles and driving cycles, or the real-time macro-dynamics of the power-train, which can have a significant effect on the long-term economic utilisation of the energy storage components. For example, the implementation of other vehicle control systems such as anti-lock braking (ABS) and traction control (TC), where transient torque control to the driven wheels is used to optimise slip between the road/tyre interface, can impact on the complementary management of mechanical and electro-magnetic braking for vehicle energy management.

Whilst it is relatively straightforward to establish optimal energy management schemes for standard driving cycles, real driving conditions will invariably result in significantly different performance, with the probability that transient battery currents will compromise both achievable range and cycle life. Fundamental issues to be addressed in order to achieve optimal energy utilisation over wide ranging operating conditions are generally applicable to many power-train formats, and include:

- the dynamic apportioning of the energy requirements between different energy storage/conversion units,
- the incorporation of economic factors, such as the impact of dynamically varying charge/ discharge profiles on the cycle life of the battery, and the battery replacement cost, into the overall energy management strategy,
- the accommodation of deviations from the optimal operating point for each energy storage unit so as to promote high efficiency, and for hybrid formats,
- the incorporation of environmental factors, such as reducing emissions due to transient throttle operation of internal combustion engine.

Over recent years, various Model Predictive Control (MPC) techniques have been devised and employed in a range of complex industrial and process control applications [3,4], a common feature being its application to problems involving plants with multiple inputs and outputs, and those with strict economic, actuator or safety constraints. The widespread application of MPC within such fields as chemical and process industries is indicative of its potential, and, whilst computationally intensive, it is anticipated that the advent of explicit solutions to the Quadratic Programming sub-problem, from efficient algorithms such as Multi-Parametric Quadratic Programming [5], will facilitate the increasing spread of MPC to high-bandwidth control systems. It is therefore considered timely to investigate the utilisation of MPC for energy management in all/more-electric vehicles, with the added flexibility to naturally scale to multi-input/multi-output systems, and the inherent ability to handle hard and soft constraints in a unified, stable manner. Indeed, constraint management, imposing specific bounds on inputs/outputs/states, is employed to provide safety limitations, satisfy environmental regulations and physical restrictions.

Although careful tuning of a classically designed controller may keep variables away from the pre-specified bounds, ideally, the control system should drive the process as close as possible towards the constraints without violating them, since, in general, this maximises the performance (and often economy) [3,4]. Constrained MPC therefore employs a more direct approach to constraint management, by modifying optimal unconstrained solutions in a manner such that constraints are not violated. Here, some of the benefits arising from the ability of MPC to accommodate constraints on input, output and system states, are considered for the case of an all-electric drive-train.

Electrical Vehicle Drive-train Configurations

For all-electric vehicles, regenerative braking is a key performance issue, since energy saving equates directly to vehicle range. However, the highly dynamic power demands typical of urban driving can have a significant impact on battery energy utilisation particularly for lead-acid technologies. Specifically, high pulsed power transients from a lead-acid traction battery, even for short durations (2-3s), can limit the full exploitation of the battery stored energy [6].

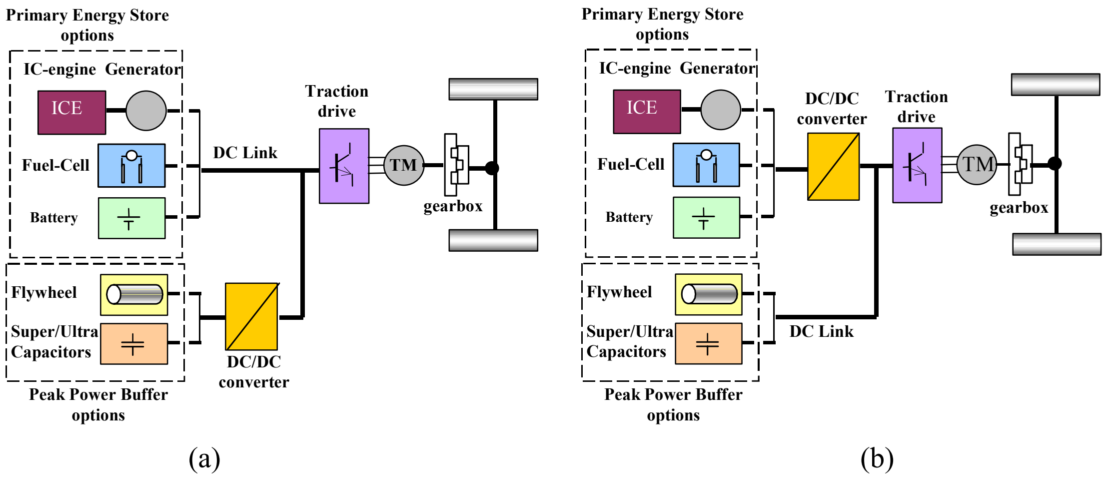

Fig.1: All-electric vehicle formats

The most commonly chosen drive-train connection schemes, particularly for all-electric vehicle formats, are illustrated in Fig.1, showing two options for interconnection of the on-board energy and power storage options in a 'series' drive-train configuration. For completeness, the position of an internal combustion engine or fuel cell in the drive-train, is also illustrated for the hybrid case. Here, the energy management philosophy is that the ICE or fuel cell fulfils a similar function to that of the electro-chemical storage battery in that it provides the vehicles average energy demand, whilst the peak power buffer provides the transient power source for acceleration or regenerative breaking. For the connection scheme of Fig.1(a), the energy store directly supplies the DC link voltage to the traction machine power electronic inverter, with the peak power buffer options connected via a DC:DC converter. In this scheme, the energy source voltage is reasonably well constrained, typically to around a 20% drop in voltage from fully-charged to fully-discharged for the traction batteries considered, with the fuel cell and ICE/alternator options having a tighter voltage regulation to ensure that they are operated within their optimum efficiency windows. Additionally, the peak-power buffer voltage can be allowed to vary to near zero, maximising the stored energy from the buffer. However, the major disadvantage of this scheme is that the peak-power buffer has to be interfaced to the traction system dc link via a DC:DC converter rated for the drive-train peaks (i.e. 45kW), which equates to a 70kVA DC:DC converter for the system considered.

Since the terminal voltage of a traction battery will vary considerably between fully-charged and discharged states, the traction drive has to be rated to cater for a wide range of operating voltages without loss in performance. Therefore, the change from the more conventional approach to one where the DC link is allowed to continually vary, as in Fig. 1(b), has minimal impact on the traction drive design. Further, a direct connection between the peak power source and traction system is more energy efficient since the DC:DC converter power handling requirements are much reduced, ideally only transferring the average vehicle power from the traction battery, i.e. ≈4-5kW. Consequently, the DC:DC converter can have a reduced silicon rating, ≈10kVA; an important commercial consideration [2,6].

To provide experimental validation of electric vehicle simulation tools whilst addressing the technical issues of drive-train component integration and investigating energy management methodologies, electric vehicle drive-train components have been assembled into a laboratory-based 'brass-board' demonstrator. The system comprises of 2×super-capacitor banks, i.e. a 135V bank comprising of 50× Maxwell cells of 2500F, and a 135V bank comprising of 300× SAFT cells of 350F, series connected to provide the dc-link for the traction system. The super-capacitor banks are interfaced with individual DC:DC converters (to account for the variation in super-capacitor specifications) to 2× Hawker sealed lead-acid battery packs. The dc-link supplies a vehicle-rated brushless permanent magnet traction machine and inverter, the mechanical output of which is loaded via a dynamometer test facility. The Maxwell super-capacitors, protection fuse and switchgear, plugs and sockets for interconnection, are housed within a 19” rack unit; likewise the DC:DC converters, DSP control platforms for the DC:DC converters and traction inverter, and energy management unit (EMU). The EMU interfaces to the power converter units via a CAN2b link. Similarly, data from supercapacitor and battery cell voltage and temperature monitors, are fed to a local PC display via CAN.

MPC for an all-electric drive-train

Initially, the energy management schemes for the experimental drive-train were relatively simple voltage tracking regulators, applying a low pass filter to the dynamic traction current demands. Whilst the scheme allows functional testing of the integrated drive-train components, it is not optimised from an energy management view-point. Fig. 2 illustrates measured data from the brass-board test facility employing such a strategy showing system dc-link voltage, traction machine current, super-capacitor and battery currents over a single ECE15 mission cycle. The results demonstrate the predicted reduction in battery current magnitude and how the simple energy management strategy utilises battery current in addition to regenerated current, to recharge the super-capacitors. However, during experimentation over various driving cycles, this simple energy management proved not to be utilising the full available power buffering capacity. Whilst acting to maintain the dc-link voltage about a pre-defined set point, any deviation above the set-point, whether as a result of short term regenerative braking effort or net energy gain over a longer period, would be counteracted with a negative control action to remove energy from the peak power buffer.

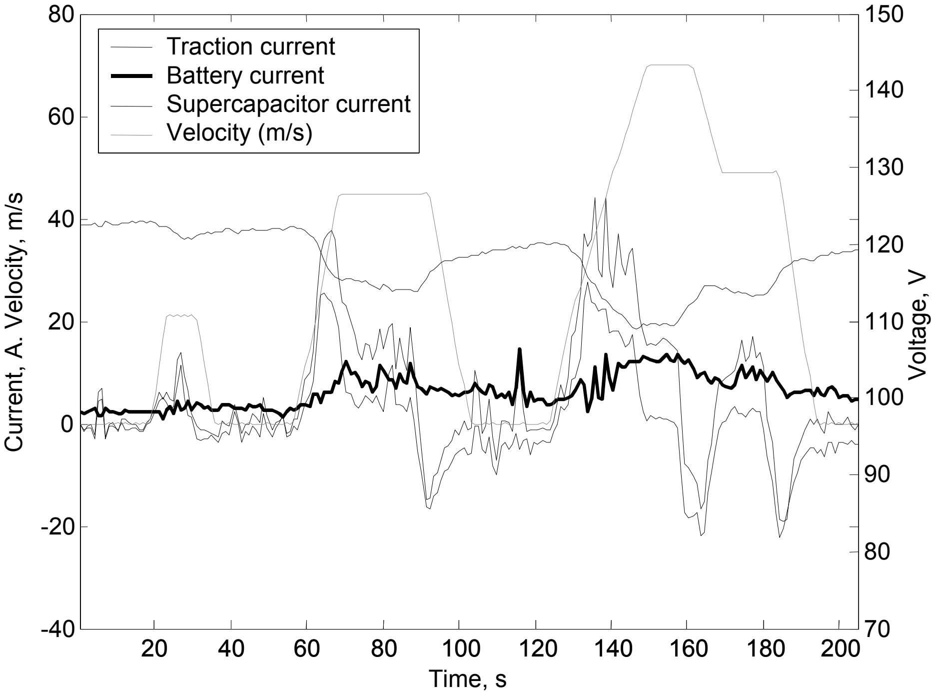

Fig. 2: Experimental results from brass-board demonstrator system

A basic MPC methodology to control the power drawn from a battery pack and a super-capacitor peak power buffer of an all-electric drive-train, is now presented. The MPC inherently accommodates the total stored energy in the system in real-time to reduce, for example, mechanical braking effort, and hence, brake wear. In addition, the recovery of regenerative energy allows improvements in overall drive-train efficiency.

Fig.3 shows a simple control model describing the dynamics of power transfer and distribution applicable to the all-electric drive-train format of Fig.1(b). To focus the study on the control of energy, internal resistances of the super-capacitors (and their associated interconnects) and thermal considerations, have been omitted. The nominal drive-train is considered to consist of a 45kW brushless permanent magnet traction machine supplied from a 400A, 600V IGBT inverter. The two supercapacitor banks each have a total capacitance, C_{sc}, of 50F, and a maximum voltage of 135V. The step-up dc/dc converters are each rated at 33kW peak with a maximum output voltage of 150V, being over-rated to provide interconnection flexibility of the brass-board demonstrator.

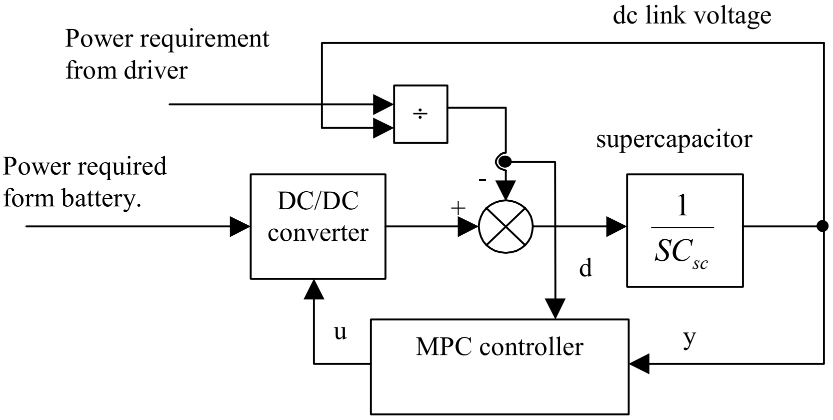

Fig. 3: Electric vehicle drive-train power flow model.

In this case, the system control requirement is to maintain the output voltage of the peak power buffer within required limits whilst ensuring uni-polar battery current, i.e. no regeneration to the battery, and minimising the battery current magnitude. The driving cycle, which is assumed to be unknown to the vehicle controller, constitutes a power disturbance to the system. A variant of MPC employing *zone control* [3,7] is adopted since the scheme is particularly attractive for this application field.

Net energy expenditure is the normal requirement for most driving conditions, and results in an overall net outflow of energy from both the peak power and the primary energy source, in this case the lead-acid traction battery pack. Since it is necessary to penalise the magnitude of current transferred directly to/from the battery pack, there is a tendency for the output voltage of the peak power buffer to approach the lower limit of the controlled 'zone'. However, when descending a gradient, for example, the net energy-expenditure requirement can reduce to zero or become negative. In this case, the peak power buffer is charged towards the upper limit of the zone, with the controller acting to remove energy from the peak power buffer only when the output voltage exceeds the upper dc-link voltage limit, thus recharging the battery. In instances when the cells are fully charged, and hence, cannot accept additional charge, or when the vehicle primary energy source does not allow for regeneration, i.e. an IC engine, or fuel-cell for the hybrid vehicle case, braking energy dissipation is realised by either resistive 'dumping' or the application of mechanical brakes.

The key difference between the proposed strategy and classical energy management that act to maintain the dc-link voltage about a pre-defined set point, is that any deviation above the set-point, whether as a result of short term regenerative braking effort or net energy gain over a longer period, would be countered with a negative control action to remove energy from the peak power buffer even when excess storage capacity still exists. Hence, although both strategies ultimately draw their energy from the primary energy storage unit to accommodate a given driving cycle demand, the simple dc-link voltage control methodology unnecessarily causes more cycling of energy to/from the battery pack, incurring energy inefficiencies, or requires more mechanical braking to dissipate the energy. Therefore, employing MPC with its inherent ability to include zone control will generally result in higher overall drive-train energy utilisation efficiency.

Zone Controller

In common with other MPC strategies, the zone controller minimises a cost function, *J*, in the presence of constraints, over [illegible]xed prediction horizon (1). This form of cost function is characteristic of Generalised Predictive Control (GPC) [8] and consists of the squared deviation of the predicted output voltage, $\hat{y}$, from the reference trajectory, *r*, and the weighted squared increment of control action, *u*. Constraints are imposed on inputs, outputs or states, eg. control actuator limitations such as slew rate, and are represented in (1) in a generalised form:

$$
\begin{aligned}
J(u,k) = &\sum_{j=Nc}^{N} \left(\hat{y}(k+j\,|\,k) - r(k+j)\right)^T \left(\hat{y}(k+j\,|\,k) - r(k+j)\right) \\
&+ \lambda^2 \sum_{j=1}^{N} \Delta u^T (k+j-1) \Delta u(k+j-1) \qquad (1) \\
&\text{subject to the linear inequality constraints} \\
&\tilde{\psi}(k) \le \tilde{\Psi}(k)
\end{aligned}
$$

where $N_c > 1$ is the control horizon, which is the prediction period for the control action; N is the prediction horizon, which is the period over which the dynamics of the system are predicted at each sample step; $\hat{y}(k+j\,|\,k)$ is the prediction of output voltage at time *k+j*, given knowledge up to time *k*; $\Delta u(k)$ is the increment in the control signal demand at each sample step; $\lambda \in \mathrm{R}$ is the control weighting factor; $\tilde{\psi}(k) \le \tilde{\Psi}(k)$ specify the constraints on inputs, output and states[4], e.g. $\tilde{\psi}(k) \le \tilde{\Psi}(k)$ might include $\Delta u(k) < 5$, which limits the slew rate of the control action to be less than $5\mathrm{A}/T_s$, where T_s is the sampling period of the controller.

Accommodating a controlled 'zone', about which the output voltage of the peak power buffer is allowed to vary, is included by appending an additional 'slack' variable $\delta(k)$ into the GPC cost function, as in (2).

$$
\begin{aligned}
J(u,k) = &\sum_{j=Nc}^{N} (\hat{y}(k+j\,|\,k) - r(k+j) + \delta(k+j))^T (\hat{y}(k+j\,|\,k) - r(k+j) \\
&+ \delta(k+j)) + \left\{ \lambda^2 \sum_{j=1}^{N} u^T (k+j-1) u(k+j-1) \right\} \\
&\text{subject to the linear inequality constraints} \qquad (2) \\
&\tilde{\psi}(\mathrm{k}) \le \tilde{\Psi}(\mathrm{k}) \quad \& \\
&|\delta(k)| \le \delta_{\max}
\end{aligned}
$$

where *u(k)* is the control signal, update every sample step, and $|\delta(k)| \le \delta_{\max}$ is an additional constraint on the slack variable (more details on this formulation can be found in [4,7]).

The additional slack variable allows the output voltage of the peak power buffer to deviate from the nominal reference value by a predetermined amount, $\delta_{\max}$, before it contributes to the cost function. This then, 'frees' the peak power buffer from the requirement of trying to control a nominal output voltage. Although other control methodologies can be 'de-tuned' to provide this characteristic, predictive control techniques readily provide an integrated framework to accommodate this feature in an optimal manner.

To develop the MPC strategy, the model shown in Fig.3 can be represented by process and disturbance dynamics, which essentially constitute the current requirements from the driving cycle, as illustrated in Fig.4, where $G = -F = \dfrac{1}{SC_{sc}}$ and are described in state-variable form by (3).

$$\begin{aligned} G &\Rightarrow \dot{x}_G = 0x_G + u_G, \quad y = {}^{1}\!/_{C_{sc}}\, x_G \\ F &\Rightarrow \dot{x}_F = 0x_F - d, \quad y = {}^{1}\!/_{C_{sc}}\, x_F \end{aligned} \tag{3}$$

Calculation of the control action at each sampling step, subject to the constraints, is well documented in [1,2,5]. However, the underlying principle is to minimise the cost function, *J(u,k)*, over an *N*-step look-ahead horizon from the discretized dynamics of (3).

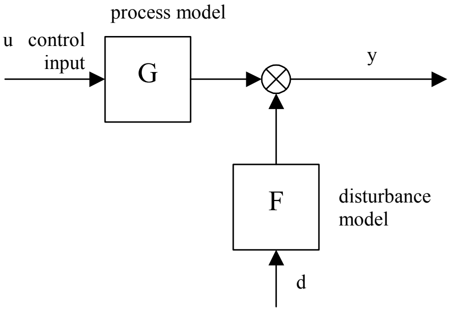

Fig. 4 Process disturbance dynamics

Results

To demonstrate the benefits of the proposed methodology, and its impact on electric vehicle braking systems, the power requirements of the standard ECE15 driving cycle is calculated from the vehicle dynamics to incorporate a negative 1.53% downhill gradient of the road. It is interesting to note that this reduces the mean power required to satisfy the nominal driving cycle requirements by 50%.

A comparison of controller induced energy flow dynamics, for the regulation of the peak power buffer voltage around the nominal operating point (classical control scheme), and the proposed MPC controller with zone control, are illustrated, respectively, in Fig.5 and Fig.6; the DC link voltage, current drawn by the traction inverter and current supplied by the DC/DC converter into the peak power buffer, simulated over 2 × ECE15 cycles, with a fixed −1.53% gradient. The prediction horizon is selected to be *N*=16, i.e. predicting 8 seconds ahead at each sample time. A cost function weighting factor of λ=1.8 is employed to provide a compromise between accommodating disturbance rejection and the magnitude of the resulting control action. From the results, it is seen that there is a significant reduction in the peak currents required from the battery pack, in both cases, by virtue of employing the peak-power buffer. However, in the case of the MPC ‘zone’ control, Fig.6, no reverse energy flow from the buffer is apparent, whereas a negative energy flow is often required from the peak power buffer to maintain the nominal output voltage in the case of employing the simple voltage control scheme, Fig.5. It is also noted from Fig.5 and Fig.6, that whilst the real-time power requirement is the same for both techniques, differences in the current requirements to the traction machine from the peak power buffer, are apparent.

The amount of energy returned to the battery pack, resistively dumped or removed by mechanical braking, is summarised in Table I for both control methodologies. The results imply that no mechanical braking is required with ‘zone’ control in this particular case, since all the braking requirements are accommodated by regeneration, irrespective of the ability of the primary energy source to accept charge, whether limited as a result of the choice of technology or state of charge of the traction battery. However, this will not always be the case, as many driving situations present much more demanding disturbance profiles, e.g. emergency stop or stopping from higher speeds, such as encountered on an ECE sub-urban driving cycle. Nevertheless, even under the most arduous braking envisaged, zone control should enhance the management of energy flow throughout the system.

Controller	Energy drawn from battery /kJ	Energy returned to battery /kJ	Net energy expenditure /kJ
MPC zone control	262	0	262
dc-link voltage control	318 (121%)	56 (21%)	262

Table I. Energy flow

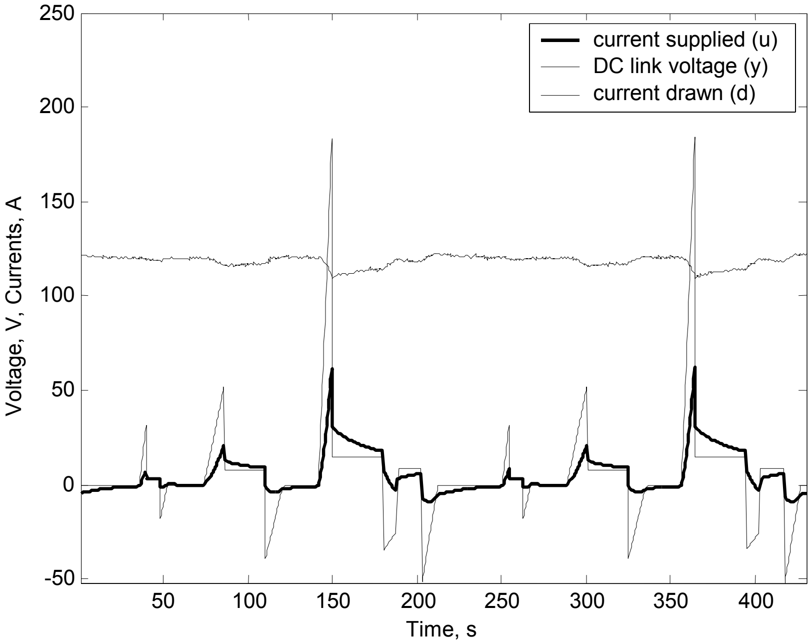

Fig. 5. ‘Classical’ dc-link voltage control

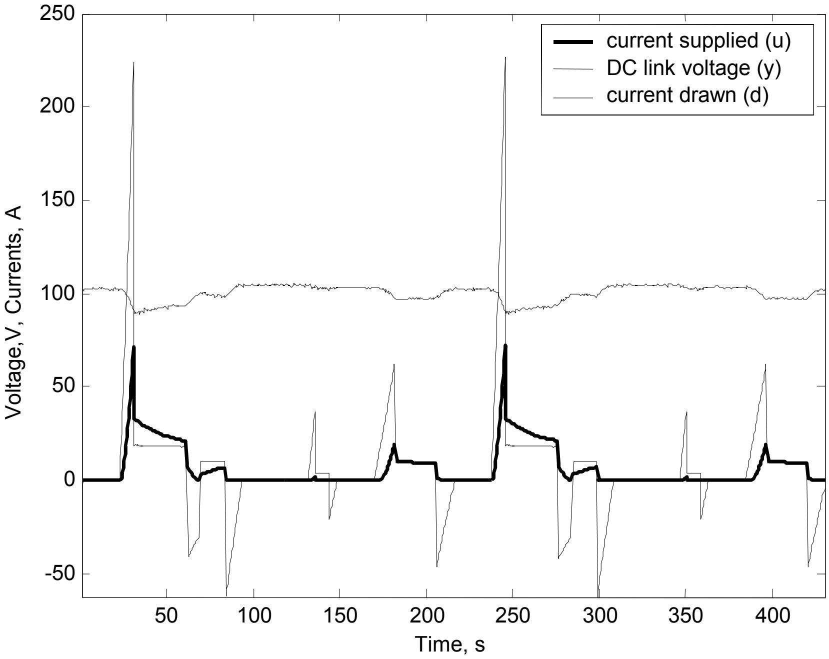

Fig. 6. Zone control

Conclusion

The paper has presented the application of model predictive control (MPC) technology to energy management of all-electric vehicles with multiple energy/power sources. It has demonstrated that, by appropriate design, the methodology can reduce transient battery currents hence enhance vehicle on-board stored energy utilisation, leading ultimately to reduced component costs and improved vehicle range. The work is currently being developed by considering optimal, and adaptive, selection of cost functions for the MPC formulation, and the application of the methodology to a hybrid-electric vehicle drive-train employing electrical torque assistance.

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