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Mechatronics in Sustainable Mobility

Two Electric Vehicle Applications*

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In this paper, we first review the role that mechatronics and advanced control have in modern road vehicles, in particular their present and potential impact on sustainable mobility. We then illustrate this with two research examples. Firstly, we show how electronic science, control system techniques and computing manifest themselves in the design of an advanced battery management algorithm designed to estimate two unmeasurable but vital quantities, State of Charge (SoC) and State of Health (SoH): this allows better utilisation of battery capacity, with scope for advanced prognostics and diagnostics. Secondly, we show how multi-domain modelling integrating mechanical science and electronic science can be used to express component ageing as part of a set of vehicle-level performance objectives and used to explore the trade-offs between conflicting requirements, aiding sensible design choices.

- **Automotive Engineering**
- **Mechatronics**
- **Electric Vehicles**
- **Battery Estimation and Health**
- **Electric Vehicle Component Ageing**

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Stringent legislative and end-user requirements on fuel consumption and emissions have led to a significant interest in Hybrid Electric Vehicles (HEVs), Electric Vehicles (EVs) and their relatives. These technologies have had a positive impact on fuel consumption and emissions, but this comes at the price of added complexity. The technologies are also radically different from 'business as usual', and new approaches to hardware and software development are needed. For Original Equipment Manufacturers (OEMs), this added complexity and novelty translates into more design, development and production work, therefore increasing costs. To keep at the forefront of a competitive market, a successful OEM needs to minimise the costs of the new technologies, yet maximise their benefits. To do this, the traditionally separate domains of mechanical design, electrical design, controls and software need to be brought together as one: this multi-disciplinary approach is called 'mechatronics'.

This paper starts by introducing the concepts of mechatronics and control in the automotive domain, discussing their evolution, their place in the design process, and their role in vehicle electrification. The paper then goes on to describe two areas where mechatronics are contributing to state-of-the-art technology research: we discuss the application of mechatronics thinking to the development of advanced battery management technology; and we discuss the use of multi-domain modelling and optimisation techniques to understand and mitigate component ageing. Concluding remarks are given at the end of the paper.

Mechatronics and its role in the automotive domain

Overview

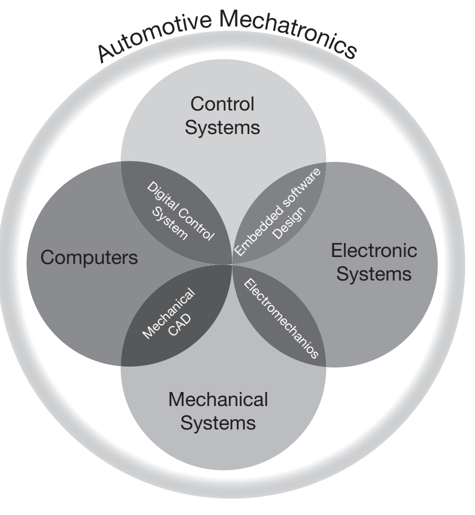
In the early days of the automobile, electronics applications were limited to entertainment systems. Only sixty years ago, the automobile was essentially a machine with mechanical controls, with electrical systems limited to a vacuum-tube AM radio, and a small amount of wiring to provide lighting functions, a horn, and a starter motor [1]. With the continuous advancement in integrated circuit technology, and hence, microprocessors and microcontrollers on one hand and the introduction of digital controls on the other, the possibility of manipulating and modifying the dynamic behaviour of mechanical, electrical and other physical systems in real-time with control software has become an established reality. The benefits of this real-time control—including increases in performance, precision, productivity, quality and reliability, ease of calibration and cost-efficiency—have drastically impacted our lives. This is particularly true of the vehicles we drive. One of the first applications of electronic controls on vehicles was the introduction of Antilock Braking System (ABS) in the early 1970s. Nowadays, as stated by one of the largest suppliers of automotive components [2], 90% of innovations in a modern car are based on new developments in electronics. Furthermore, these innovations are rarely pure electronic systems such as information processing and navigation systems. Most of them are based on mechatronics [3].

The ever increasing interest in utilising electronics in real-time control of mechanical systems resulted in a specialised domain of mechatronics. Mechatronics is the synergetic integration of physical systems (mechanical, hydraulic, and pneumatic), electronic systems and digital control, through a design and development process. This process is a key enabler for complex decision making. The multidisciplinary domain of the automotive mechatronics is shown in Figure 1.

There is an ever-increasing demand for mechatronics in a car. The major areas which are impacted by mechatronics are as follows: the propulsion system, the chassis system, the body and interior systems.

This demand in mechatronics is driven by legislative and end user requirements. Some of these requirements are fuel consumption, emissions, improvement in driving performance, comfort, and safety. However, simultaneously, this demand introduces some major challenges and some opportunities. In the automotive domain, the control software development and design process is adopted from the aerospace industry, but unlike the aerospace industry, the process is not standardised and is in state of flux. In addition, lack of expertise and structure makes this a very costly business for automotive OEMs. In the automotive business environment where cost competitiveness is the only way to survive, this is a very tough challenge. The roles of suppliers and automotive OEMs are not as clear cut as before, which results in another challenging aspect of bringing these technologies into production.

Figure 1 Mechatronics: a multidisciplinary domain



The development process: from requirements to modelling and control

The field of mechatronics is not new as the experts in robotics and artificial intelligence have been familiar with such concepts for decades. However, in the automotive field, the term 'mechatronics' has not yet been fully understood. The automotive OEMs are more familiar with system engineering than automotive mechatronics. The two areas are fundamentally different. **System engineering** focuses on managing multidisciplinary projects with emphasis on tools and processes. **Mechatronics** focuses on developing the actual design by integrating multidisciplinary domains.

As automotive OEMs are traditionally mechanically oriented, they favour decoupled structures such as powertrain, electrical, chassis, body and so on. Hence, the development processes are set up around these decoupled units and the increasing demands for mechatronics and vehicle electrifications, such as hybrid powertrains, require coupling and integration of these very same decoupled units.

The development processes that are utilised in vehicle mechatronics projects are still very mechanically focused with control and electronics still viewed as afterthought add-ons. We will discuss in more detail the existing development process (from **requirements** to **modelling and control**) including gaps and potential possibilities for integration of mechanical and control development.

Requirements

Requirements are a contract between stakeholders. The main driver behind writing requirements is minimising the production time by assuring all failure modes are avoided at later stages of the development and production process. The Design Failure Mode and Effects Analysis (DFMEA) is the backbone of the production development process of major OEMs. The traditional DFMEA started with an initial design and then a prototype building. In modern DFMEA, another step is included in between: this is called design verification. This modern approach relies heavily on virtual modelling and design verification to capture failure modes at the early stages of design using the virtual environment.

The DFMEA process has had a very positive impact in streamlining the hardware development process and hence, shortening the production time. However, when it comes to mechatronics system development, this process has some shortcomings. Models utilised at early stages are normally of low fidelity, which makes it difficult to capture failure modes. Furthermore, the entire process is set around hardware development and the impact of control software is not understood in detail. The control algorithms are very immature and simple at the early stages of design and they are not good representatives of the final design. Furthermore, the entire DFMEA process is very hardware based and this process does not lend itself easily to a more unified mechatronics design approach.

The above are only some of the fundamental issues with the production development process currently utilised by major OEMs.

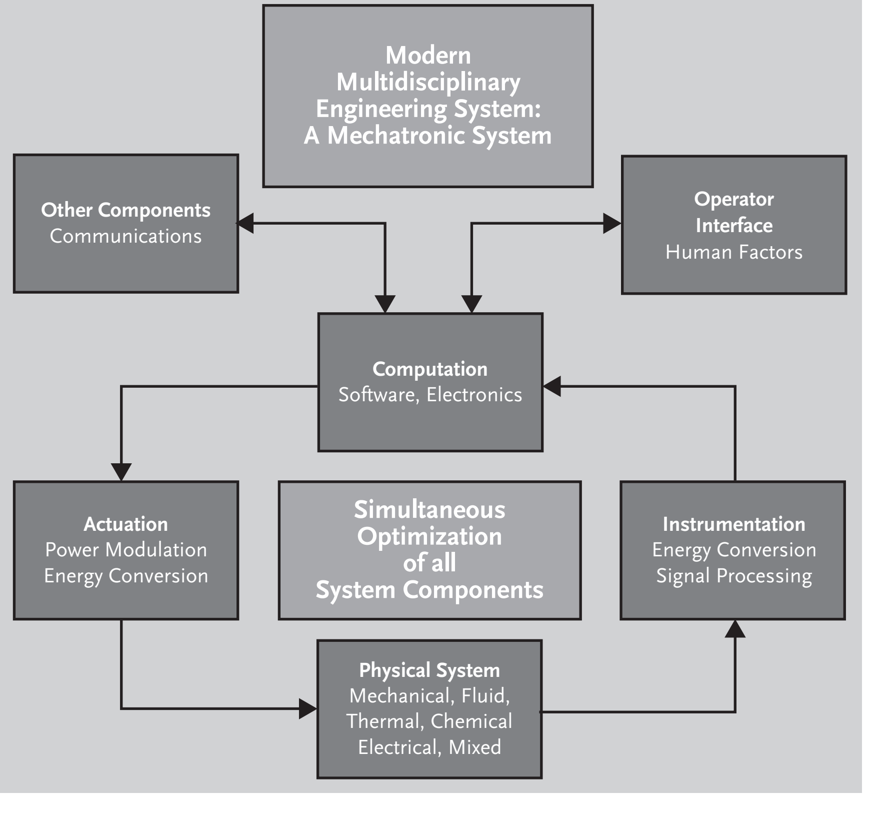
Modelling and control

Based on the previous discussions regarding the use of the virtual environment for reducing production time and avoiding failure modes, it should be evident that mathematical modelling plays a very important role in mechatronics system development.

Modelling and control are dealt with as two different domains. Control systems are designed separately and added on for evaluation of the system characteristics and performance. The approach is normally 'one model fits all' rather than understanding and utilising different modelling techniques for different purposes. The question of 'what is the purpose of a model' is never asked.

The intent of an engineering project is to deliver a better product at a lower cost. Hence, a proper control design has a significant role in accomplishing this goal. It is very difficult, if not impossible, to accomplish this goal when the control design and modelling are dealt with as decoupled identities and entire systems are not optimised together. As pointed out in [4] and illustrated in Figure 2, 'a real mechatronics approach requires that an optimal choice be made with respect to the realisation of the design specifications in the different domains'. Thus, control and model evolution has to happen together. More precisely, evaluation of any changes in the physical system and controller has to be done simultaneously. Physical modelling techniques, which are based on multi-domain energetic approaches, such as bond graphs [5], are excellent tools for mechatronic system design and development.

Figure 2 A mechatronic system [4]



When it comes to control, there is a tremendous potential for improvement over current strategies. For example, the electronic engine management systems utilising engine torque as a common denominator (so-called 'torque manager') have emerged as indispensable tools for meeting legal requirements, such as emissions and fuel consumption, as well as improving drivability of engines, e.g. start, warm-up behaviour and transient response. However, as the number of actuators which could influence tractive forces increases (e.g. hybrid vehicles), the current engine torque structure has to be modified. Up to now, the majority of suppliers and OEMs have pursued an ad hoc (also called 'pragmatic') approach to cope with these modifications. However, these ad hoc approaches do not fully utilise the capabilities of a more complex powertrain to optimise fuel efficiency, emissions, and drivability. In addition, the trade-offs between the aforementioned measures are not fully understood. This results in tremendous opportunities in the controls domain in terms of research and development.

Estimation and optimisation for electric vehicle battery management systems

Overview

This section will focus on a particularly important mechatronic application: Battery Management Systems (BMSs). Large batteries for EV are delicate and expensive devices. Nevertheless, they have to be pushed to their performance limits for EVs to be competitive market options. Responsible for the safe and efficient operation of the battery is a computing unit with sensing, actuation and communication capabilities called BMS. Developing BMSs is critical for manufacturers who would like to increase the market share of their products. The ability of BMSs to simultaneously minimise the risk of battery damage while efficiently use its energy relies upon:

- Accurate but tractable mathematical models of the battery chemical, electrical and thermodynamic processes
- Sophisticated but implementable algorithms for the estimation of immeasurable or uncertain quantities such as the battery state of charge
- Reliable and practical algorithms to optimally trade off battery degradation and energy efficiency

There are fundamental trade-offs that need to be understood and acted upon. One is computational. Although accurate mathematical models and sophisticated algorithm are desired, the computational power of the BMS computing unit and the ability of introducing extra sensors and actuators are constrained by financial costs and the physical space available inside the battery pack. Where is the threshold where the benefits of complex algorithms and BMS configurations outweigh the cost of the BMS? Another trade-off comes from the vehicle's energy management. Although responsiveness to drivers' inputs (acceleration and regenerative braking deceleration) is desired, sharp changes in the battery energy flow (charges and discharges) deteriorate it more rapidly. Where is the optimal point where battery degradation is minimised while good drivability and high-energy efficiency is maintained? Answers to these questions require a highly interlaced collaborative effort among chemists, electrical/electronic engineers and control engineers.

The performance of estimation algorithms is vital for the correct functioning of batteries in electric vehicles, as poor estimates will inevitably jeopardise the operations that rely on unmeasurable quantities, such as State of Charge (SoC) and State of Health (SoH). SoH here is defined as battery capacity fade. BMSs are embedded computers that have the ability to execute real-time algorithms in order to estimate, control and communicate with other components. Implemented into EVs, BMSs manage the battery by monitoring its state, protecting the battery and controlling its environment [6]. Estimating battery's state provides information that is essential for obtaining critical variables such as the SoH and SoC of the battery. The estimated state of the battery determines the control actions that will be taken by the BMS and enable a more aggressive utilisation of the battery, while ensuring its safe and reliable operation [7].

Over the past decades, different versions of battery models have been applied in combination with a number of estimation algorithms. The first category includes equivalent circuit models (ECMs), which consider the battery as if it was an electrical network. The majority of battery models are based on ECMs as they represent complex relationships in a simplified way, aiding the calculations and the analysis.

The second category consists of the electrochemical models, battery models that are represented by partial differential equations and provide an explanation of the fundamental physics of the batteries. Electrochemical principles to model a lithium-ion (Li-ion) battery with a reduced-order model are used in [8]. In [9], the same authors, based on the analytical expressions of a Li-ion battery, present a simpler electrochemical model, which is used to design an observer. Such a modelling method is complicated, as it is difficult to obtain the model's parameters and it is not computationally suitable for online estimation.

In this paper we consider Li-ion batteries, which are recognised as the most promising technology [9]. As well as being among the batteries with the best energy-to-weight ratios, they have the privilege of lacking memory effect and when they are not in use their self-discharge rate is low. Additionally, their decreasing cost enlists them as a leading candidate for the next automotive generation [8]. The battery model that is chosen to represent the Li-ion battery belongs to the ECMs category and is known as Thevenin model. The estimation algorithms that have been compared here to estimate the states of the Li-ion battery are the Extended Kalman Filter (EKF), the Unscented Kalman Filter (UKF) and Particle Filter (PF). The algorithm's accuracy is tightly coupled with its computational complexity.

We will analyse the complexity of the EKF, UKF and PF based on their number of operations and the execution time (i.e. their computational effort). The trade-off between estimators' performance and computational complexity is shown. This could be used for the selection of the most appropriate estimation technique for a particular application.

Estimation algorithms

Estimation algorithms are mathematical techniques used to compute the optimal estimates of states and parameters of a dynamical system. Here, we use them to estimate the states of a Li-ion battery cell, which cannot be directly measured.

In the EKF, the nonlinear dynamical system is linearised at every time step by a first-order Taylor-series expansion approximation. The linearised system is then used to compute the estimation of the states and the error covariance matrices. The EKF is easy to implement in terms of complexity, especially when the linearised system matrices (Jacobians) can be computed analytically. Its simplicity makes it a tempting choice among the variety of nonlinear estimation algorithms. However, the EKF's performance deteriorates when models are highly nonlinear. The UKF, on the other hand, can better deal with nonlinearities.

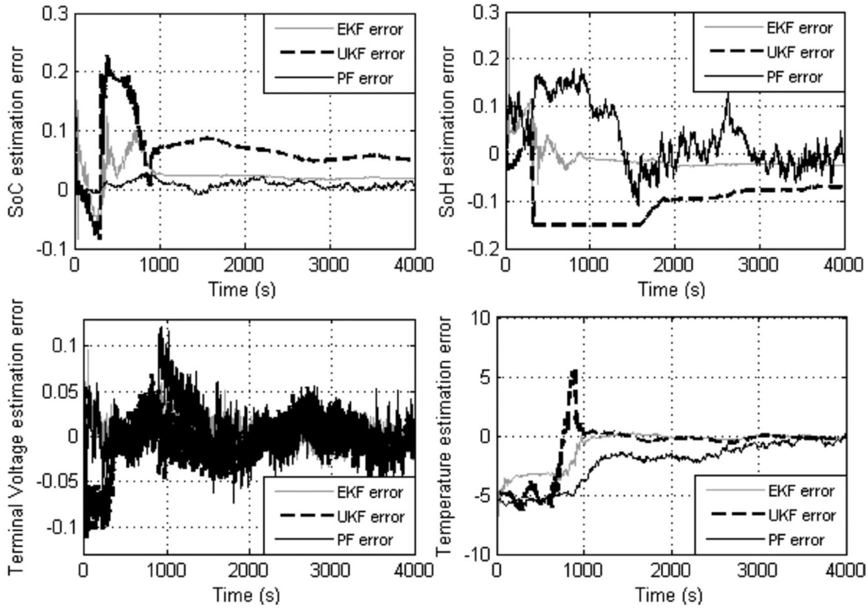
The UKF attempts to propagate the mean and the covariance values of a system using the methods of time update and measurements update. According to this, when systems under consideration are highly nonlinear, the method of linearisation based on the EKF does not seem to be the ideal solution. The UKF determines a set of points (called sigma points) and transforms them nonlinearly to a new set of points. Due to this, the mean and covariance value of the sigma points matches the mean and covariance value of the estimated value. The states of the system and the covariance matrices are computed based on those sigma points.

Both the EKF and UKF work under the assumption of a Gaussian noise distribution, limiting the range of their applications and characterising them as inappropriate for non-Gaussian dynamical systems [10]. The PF algorithm works on a different philosophy. Being part of the sequential Monte Carlo methods, the PF estimates states and parameters of a nonlinear dynamical system using a number of sample points based on Bayesian estimators.

Performance comparison

It should be noticed that the cell model used to simulate the 'real' battery cell is also used within the estimation algorithms to compute the estimated values. This provides an advantage in the entire estimation procedure, as the estimators operate under ideal modelling conditions. However, in the model for the 'real' battery, a Gaussian noise with variance equal to 4 is injected to the input and output signals.

Figure 3 Estimation algorithm performance comparison [11]



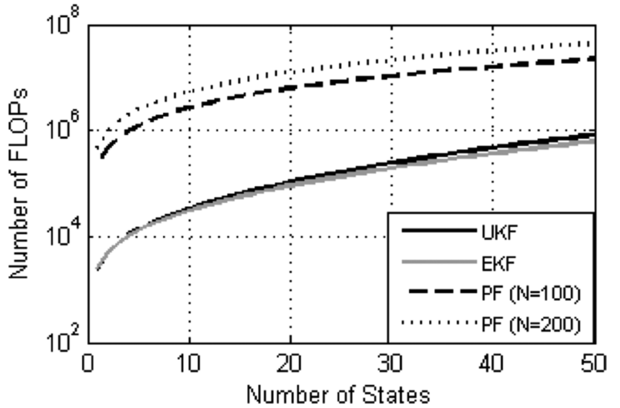
The analysis of the algorithms' performance focuses on the estimated values of SoH, SoC, temperature and terminal voltage (see Fig. 3). The sampling time was selected to be 1 s, which is appropriate given the relatively slow dynamic response of the battery. Each graph contains the estimated values from the three filters (the PF is implemented for 100 particles).

As can be seen in the plots, the SoC and voltage estimations seem to have a faster convergence rate than SoH and temperature, which also converge but at a slower rate. The reason may be that slowly changing states (as the SoH) and parameters (as the temperature in this case) are generally more difficult to track. Overall, the EKF appears to have a better performance and be more accurate when compared to the other filters. However, at steady state, the EKF and the UKF converge to the same estimate. The superiority of the EKF to UKF has to do with the types of nonlinearity that characterise the cell model and the fact that the noise affecting the system is precisely known (see [11] for the details). The model for the Li-ion cell is only moderately nonlinear. The UKF approximates the Gaussian noise distribution rather than the model. With a mildly nonlinear model and known noise distribution it is not surprising that the EKF, which approximates the model instead of the noise distribution, performs better than the UKF. The PF seems to have higher accuracy, as far as SoC and voltage are concerned. The reduced performance in SoH and temperature estimation may be due again to the noise distribution. PFs perform better for non-Gaussian systems but the noise added to this particular model is Gaussian. Further work will include experiments with models corrupted by non-Gaussian noise.

Estimate accuracy is an important criterion on which the choice of the algorithm is based. However, accuracy and computational complexity are correlated and both of them have to be taken into account when evaluating the algorithms' performance. Computational complexity will be analysed in terms of the number of operations performed in the algorithm and the corresponding execution time. In order to determine the number of operations executed in the algorithms, the number of FLoating-point OPerations (FLOPs) will be introduced. The FLOPs are indicative of the complexity of each algorithm and constitute a measure of comparison.

Taking into account that every embedded computer has a different range of capabilities and that for a typical processor more than one step is needed to execute one operation, it is assumed that all the operations have the same weight and each operation (addition, subtraction, multiplication, division and square root) corresponds to one FLOP. Keeping as a constant the number of inputs $m = 1$ and the number of outputs $p = 1$ and varying the number of states (for example by adding more capacitors in the battery model for higher accuracy) the graph in Figure 4 is produced. It can be seen that as the number of states increases, the number of FLOPs increases rapidly, especially for the PF. For $n = 4$, which is the number of states of the proposed cell model, the total number of FLOPs for the EKF is 10,217, for the UKF is 10,414 and for the PF is 964,603 (N=100) and 1,929,203 (N=200). It should be noted that the complexity of the PF, even for N=100, is approximately two orders of magnitudes higher than that of the EKF, making it challenging to use the PF for real-time estimation.

Figure 4 Number of FLOPs for the EKF, UKF and PF [11]



This analysis (FLOP counting) is theoretical and only gives an indication of the algorithms' complexity. In practice, the actual execution time is needed, and this can often only be obtained experimentally. Hence, the actual execution time of the three filters was measured experimentally. The computation was performed on a desktop PC with a 2.1 GHz CPU, 4 GB of RAM and running MATLAB 2011a. The execution time for the UKF and the execution time for the PF are 2.4 and 35.2 times longer than the one for the EKF, respectively. The time difference between the PF and the other two algorithms is very large, considering that these estimations should be executed online and within a typical sampling interval of 1 s. This result confirms the high complexity of the PFs that was predicted, theoretically, by counting the number of FLOPs.

Understanding and mitigating component ageing in hybrid and electric vehicles

Estimation is one example of the way in which mechatronics can aid the development of lower-emission road vehicles.

A second example application is in the understanding of component ageing and in the optimisation of vehicles to achieve appropriate compromises between cost, efficiency and longevity.

Vehicle longevity

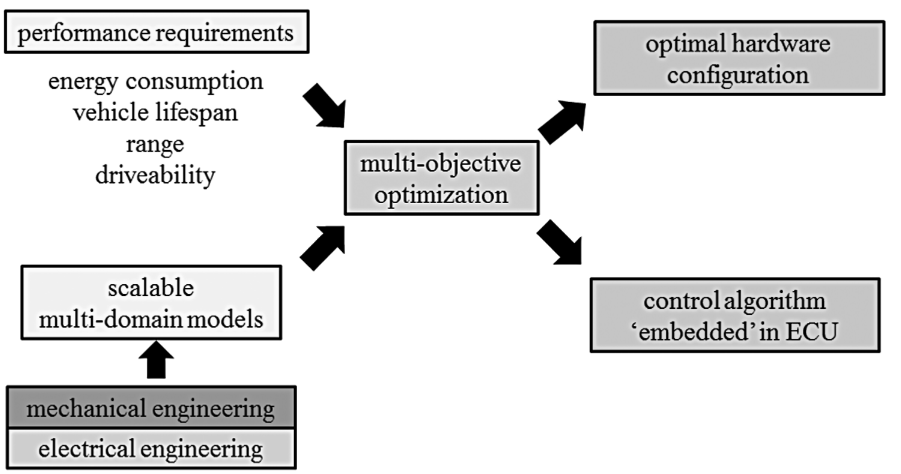
Readers will be well aware that passenger cars are neither expected nor designed to last forever. In a traditional internal combustion engine vehicle (ICEV), the maximum possible lifespan is typically determined by the longevity of the engine; in a hybrid or electric vehicle, the lifespan is expected to be determined by the longevity of the vehicle's traction batteries. These batteries cost several thousand pounds—comparable to an ICEV's engine—so they represent a significant part of the vehicle's cost and manufacturing CO_2 footprint. It has been shown that the CO_2 emissions associated with the production of an electric vehicle account for a significant part of its lifecycle cost [12]. It has also been shown that with the present European electricity mix, the net reduction in CO_2 emissions depends heavily on the vehicles' lifespans: a lifespan of 200,000 km, say, represents a significant CO_2 reduction compared with a modern ICEV, but if this lifespan is halved to 100,000 km, the reductions are modest compared to gasoline ICEVs and non-extant compared to diesels [13]. To ensure that the theoretical environmental benefits of EVs are realised, it is necessary to ensure that they last at least as long as—if not longer than—our current petrol and gasoline vehicles. It is also important to ensure that an EV is a 'good buy' compared to an ICEV, otherwise it will not represent good value for the consumer. Earlier in this paper we discussed battery 'State of Health' in the context of estimation. Here, we will discuss it again, but this time the focus is on understanding what causes the SoH to fall. If we can understand degradation and mitigate it, we have the potential to do something to address it. Similarly, the HEV/EV motor and Fuel Cell EV fuel cells are important in determining a vehicle's lifespan. This is a classic mechatronics problem: to understand it, we need to understand the interactions of various electrical and mechanical systems, and their behaviour in the presence of real-world driving behaviour. Having done this, we then need to ensure our components are correctly sized and that we have the best possible combination. We also need to design appropriate control laws. It is possible to approach the problem in an ad hoc way. However, by considering all aspects at once, we can guarantee the best possible solution. A workflow achieving this is illustrated in Figure 5.

Defining performance requirements

The first step in the production of any optimal vehicle design is the definition of a set of performance requirements: this is implied in the term 'optimal'. Typically, performance requirements will include:

- Energy consumption—for a pure electric vehicle, this is usually stated in SI units of power or kWh; for an ICEV or non-plugin HEV, it is usually given in litres per 100 km
- Range (between charges)
- Driveability—often specified as the time taken to accelerate from rest to 100 km/h
- Vehicle price—usually in absolute terms

Figure 5 Workflow for vehicle optimisation; the designer is able to balance conflicting performance requirements in order to achieve chosen design objectives

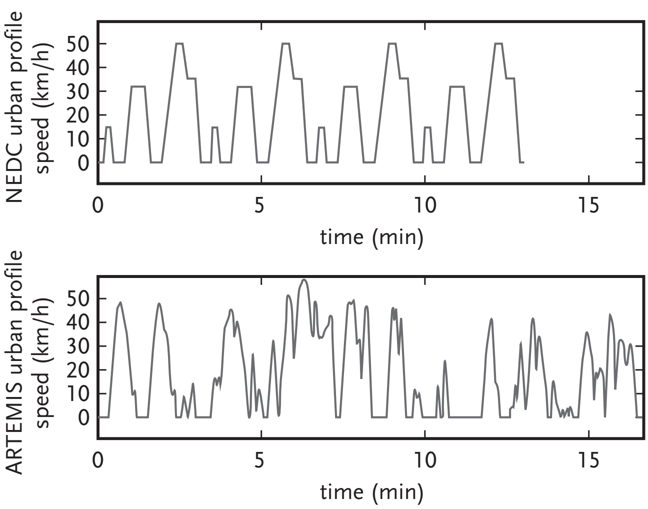


If we are interested in factoring ageing into this, we need to introduce another aspect, 'lifespan'. Equipment lifespan can be measured as an absolute—in multiples of 1000 km, say— or in terms of providing 'good value' when the vehicle price and running costs are 'amortised' over the absolute lifespan. We suspect that both of these measures are important: consumers want cheap cars, but they also want them to last well. In the UK, at least, there seems to be an expectation that gasoline ICEVs should last at least 150,000 km. It would not be surprising to find similar demands from the EV consumer. The way energy consumption and range are measured is often constrained by legislative requirements—at least for official purposes. In Europe, it is currently a legal requirement that manufacturers use the 'New European Driving Cycle' (NEDC) [14]. While this does ensure that all vehicles are tested using a common framework, the NEDC is not perhaps ideal: its time-velocity profiles are stylised, and perhaps not representative of modern driving; other cycles—such as the Artemis cycles [15]—are perhaps better. The difference between the urban sections of the two is illustrated in Figure 6. In order to be confident that a vehicle will last for an advertised lifetime, it is sensible to choose a driving cycle that is representative of real-world usage. There are many cycles to choose from, but there are good reference sources that will help guide the interested reader to the most appropriate ones [16]. Each given performance requirement can be treated as either an absolute constraint (which must be satisfied, or else the solution is not considered viable) or as part of an objective function which must be optimised. If there is more than one requirement expressed as objectives, then the trade-off between them can be explored. An example set of constraints for a C-segment EV might, for example, include the following:

- Range: at least 150 km between charges
- Driveability: rest to 100 km/h in no more than 11.5 s

One could then explore the trade-offs between energy consumption, vehicle price and vehicle lifespan. This is, of course, just one possibility, and there is plenty of scope for adding further detail, e.g. different minimum ranges for different types of driving.

Figure 6 Driving cycles for performance requirements; the urban section of the New European Driving Cycle (NEDC), top, is often invoked by statutory requirements, but other cycles such as the Artemis Urban cycle [15], bottom, provide a greater degree of realism

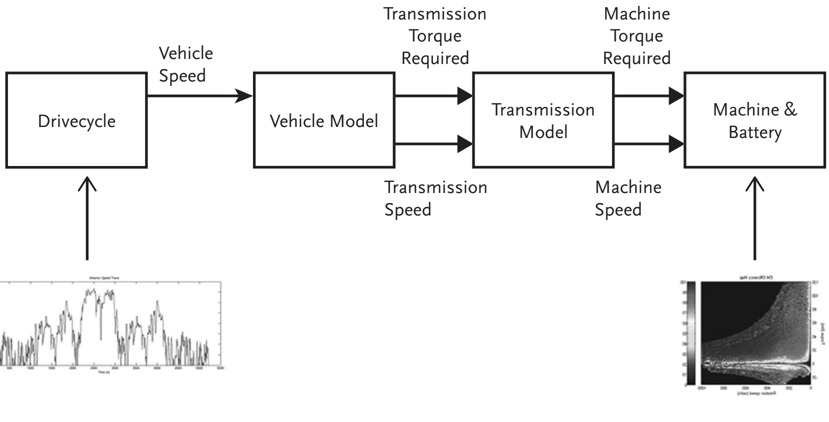


Developing vehicle models

Techniques for the estimation of a vehicle's fuel and/or energy consumption are well-established and at least one excellent book has been written on the subject [17]. The basic approach is to construct a 'backwards' model of a vehicle that computes power demands as a function of pre-determined 'driving cycles' (time-velocity profiles). The models are called 'backwards' models because they differ from the most common type of model: a 'forwards' model applies forces and observes the resulting motion; a 'backwards' model does the opposite. Backwards models typically use simplified representations of component dynamics: this makes them run quickly, which is very useful if the models are to be run many times as part of an optimisation exercise. Although there is a loss in fidelity compared to a detailed 'forward model', this does not seem to be a serious limitation in practice. There are workflows in existence which combine forwards and backwards modelling to good effect [18], and at least one source [19] suggests that the extra fidelity present in a 'forward' model is not needed, at least in the initial component-sizing optimisation stages. A schematic for a model of a typical EV powertrain is illustrated in Figure 7. Details are available in many sources, e.g. [17].

For the assessment of vehicle lifespan, it is critical to have a good model of component degradation. Some battery models are available, e.g. [20], [21]. Similar models are needed for other components such as electric machines and fuel cells. By placing such a component ageing model in the context of a full vehicle simulation, the relationship between ageing and the chosen driving cycle can be explored. The current demands placed on the battery will be realistic, and—if the driving cycle is chosen to be relevant—reflective of those encountered in real-world driving patterns.

Figure 7 Schematic for a vehicle powertrain model; this can include mathematical representations of system behaviour and non-linear performance maps



Multi-objective optimisation

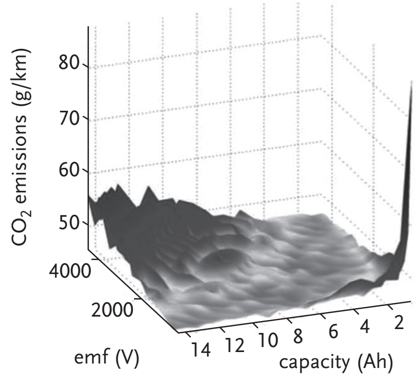
Having defined a set of performance requirements and derived a scalable vehicle model, it is possible to use a multi-objective optimisation technique to find a set of optimal solutions: the solutions are effectively 'Pareto optimal', each representing a point on a curve, surface or hyper-surface describing the trade-offs between the different objectives. By deriving such surfaces, the designer is able to understand the interactions between the objectives and select one or more appropriate design points. When doing so, it is important to consider the sensitivity of the results—if a small change to the model results in a big change to its behaviour, the design is unlikely to be robust. There are formal mathematical techniques for sensitivity analyses, and these may be used to identify aspects of a model that will have the biggest impact.

An example of a multi-objective optimisation exploring the trade-offs between the sizing of a battery pack in terms of vehicle price, energy consumption and vehicle lifespan using an assumed (but sensible) battery degradation model is presented in [21]—an example of the trade-offs produced is shown in Figure 8. Further work is being conducted in these areas, notably in the extension of the optimisation to the sizing of other vehicle components (not just the battery!) and in the use of parallel supercapacitors. (Some work on supercapacitors is presented in [21], and present work is extending this to create a single, integrated optimisation with optimised control trajectories.)

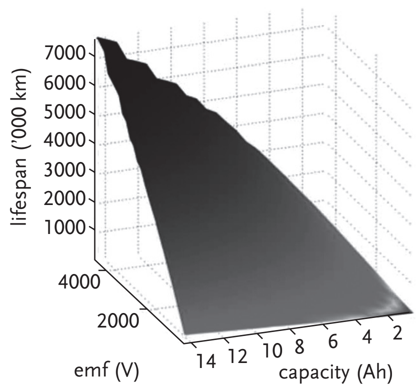
Conclusions

Automotive mechatronics applications have been made practical through the continuous improvement of semiconductor and microcontroller technologies. As the advancement of semiconductor and microcontroller technologies continue so will the increase and complexity of automotive mechatronics. This complexity results in many challenges for both automotive OEMs and suppliers. Among these challenges, a better definition of roles of suppliers and automotive OEMs, more efficient development processes, more expertise in the mechatronics area especially on the OEM side, use of advanced control techniques, and more refined integration approaches are worth mentioning. These challenges open up the door to many opportunities for experts in the domain from academics to small businesses to meet these challenges in a timely fashion. The key competitive differentiators of tomorrow's vehicles will be in the control software.

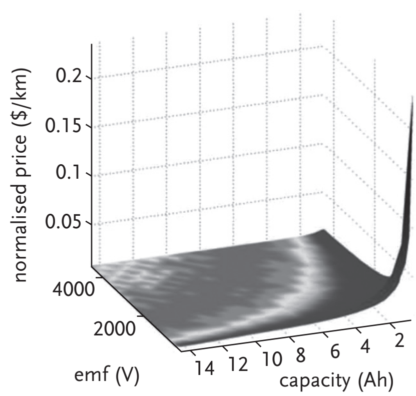
Figure 8 Variation of the vehicle performance measures with battery array size; these plots show how the CO_2 emissions, lifespan, and powertrain cost per unit lifespan vary as functions of the battery size [21]



(a) CO_2 emissions vs battery size



(b) Lifespan vs battery size



(c) Normalised cost vs battery size

Two mechatronics research problems were presented: battery estimation, and understanding and mitigating component ageing in HEVs and Battery EVs. For the estimation problem, results showed that the EKF algorithm, although based on an approximation of the nonlinear dynamics, was generally more accurate than the UKF and PF algorithm. This was probably due to the fact that the UKF, which is based on an approximation of the noise distribution rather than process dynamics, performs better for highly nonlinear systems and the cell model considered was only mildly nonlinear. The computational complexity of the PF is up to two orders of magnitudes higher than the other two methods and its practical applicability would be difficult to justify for the model used here.

For the component ageing part, we have outlined a method of describing component ageing through models and their associated performance requirements. We have briefly described the techniques used to represent driving cycles and create vehicle models. We have then shown how these models are used to perform multi-objective optimisation, allowing us to explore and understand the Pareto-optimal trade-offs between component ageing and other performance characteristics (e.g. energy efficiency). Finally, we have described existing work considering battery degradation, and we have indicated future directions.

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