ELECTRIC DRIVETRAIN ARCHITECTURE OPTIMISATION FOR AUTONOMOUS VEHICLES BASED ON REPRESENTATIVE CYCLES

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1. Introduction

As vehicle manufacturers adopt and integrate electric propulsion throughout their fleets, the costs associated with misguided decisions are increasingly large in such a competitive marketplace. The traditional tools and processes utilised to design and optimise powertrains have not necessarily kept up with updated technology, and the changing needs of the industry. In their rawest forms, the traditionally processes remain time consuming and fragmented, and overly dependent on subjective views, or unconscious bias towards 'known solutions'. As a result, these processes make it challenging to objectively answer "what is the best electric powertrain for a given vehicle?".

A fully considered system approach is required to begin to answer this question, and it is this philosophy that has driven the development of tools at Drive System Design (DSD). The Electrified Powertrain Optimisation Process (ePOP) allows thorough mapping of the potential design space of electric powertrain options. The key enabler to this process is the characterisation of subsystem and component design, allowing the process to build complete powertrain variants for simulation. ePOP rapidly generates the necessary input data (masses, efficiency maps, etc.) for each electric powertrain subsystem for a range of topologies and layouts. The rapid generation of input data permits the simulation of a large number of powertrain combinations, compared through intelligent cost functions and trade-off algorithms. This allows trade-off evaluations of cost and efficiency (or vehicle range), both of which are key to the future of electric vehicles.

In this paper, ePOP and the effect of a system approach is demonstrated through the optimisation of an electric powertrain for an autonomous electric vehicle. The optimisation of any powertrain through simulation is defined through the constraints and minimisation targets. When considering an autonomous vehicle, defining each performance target compared to a traditional vehicle becomes an interesting task with a wide range of implications. To narrow the possibilities, this paper will consider the optimisation of an electric powertrain for both a traditional and an autonomous family SUV, which are required to do both city and highway driving. This will both identify the benefits of the approach, and the impact of autonomous driving on powertrain decisions.

2. Optimisation Process

ePOP is a holistic powertrain optimisation tool which encompasses the modelling of each powertrain subsystem and vehicle modelling within a single simulation process. By enabling the tool to do so, it can quickly generate a large number of powertrain variants, unaffected by experience, opinion or bias. Each variant can be used in vehicle performance simulations, allowing quantifiable comparisons, and identification of trends. The user need only define the vehicles parameters, such as mass, aerodynamic and rolling resistance coefficients, and the performance targets to allow the process to define the optimal powertrain for either cost or range.

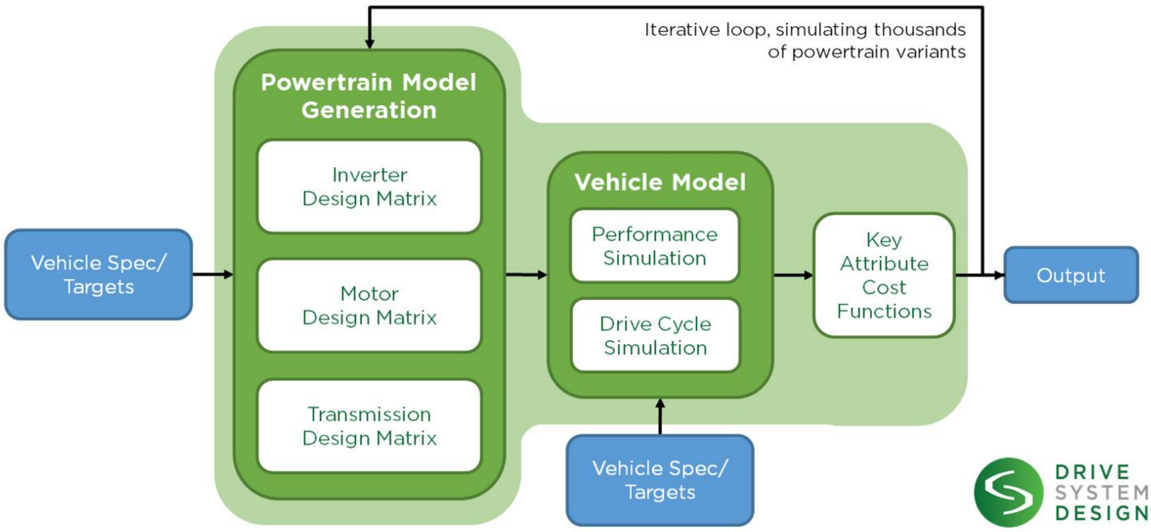

Figure 1: DSD Electrified Powertrain Optimisation Process (ePOP)

Figure 1 illustrates the overall process where the vehicle specification and targets are not only inputs to the vehicle model, but also used to intelligently define and limit the range of powertrain subsystems to be analysed. The selected powertrain combinations are simulated to analyse the performance of the electric vehicle and the range over a number of drive cycles. Subsystem data and results from the vehicle simulation can then be used in a number of cost functions. As ePOP has generated each subsystem specification itself, sufficient data is known about the subsystem and its constituent components to determine accurate relative costs. The information provided by adopting an analytical system approach gives the user the ability to understand complex trade-offs. An accurate assessment of cost versus range allows the user to explore the design space and determine the best powertrain for the given application.

3. Subsystem Modelling

A key feature of the process is the ability to rapidly and accurately model subsystems and components, to create input data for a range of inverter, electric motor and transmission variants, tailored to the requirements of the application. The process generates each subsystem's characteristics, required for the vehicle simulation and cost functions. Each subsystem model generation process is explained in detail in the following section.

3.1. Transmission Model

The transmission subsystem modelling procedure enables the generation of input data for any characterised transmission architecture. A modular approach is adopted where the transmission is broken up into systems of parallel shaft and planetary sets which can be connected in any way to generate a plethora of transmission architectures. Components such as gears, shafts and bearings are primarily sized based on torque and gear ratios that act as multipliers. For example, gears are sized by determining input torque and requested ratio. Whilst the detailed design of a gear pair is a complex process, factors impacting size and power loss are more limited. By controlling key design parameters, the gears' size can scale for torque and ratio, maintaining stress targets based on ISO standards. Multi speed transmissions can be included by adding in systems such as clutches, sized using similar methodologies.

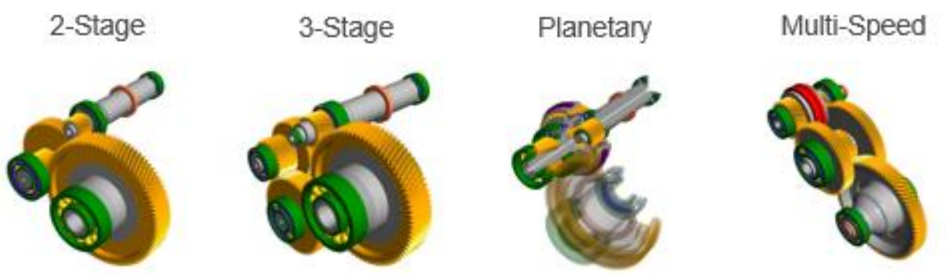

Figure 2: A selection of transmission systems which can be considered

Once sized, the masses of transmission internals, gears, shafts, bearings and clutch packs, where relevant, can be determined relatively simply. A comprehensive algorithm is used to calculate an accurate casing size, and therefore mass, for each transmission. The moment of inertia of the system is calculated through the mass and geometry of the system components. A cost is given to the raw material mass of aluminium, steel, and actuation systems, with cost functions for machining and manufacturing.

The subsystem model for each transmission outputs an efficiency map, cost, mass, and moment of inertia. The efficiency of each transmission is based on the mesh losses, loaded and unloaded bearing losses, churning losses and seal losses. Clutch drag losses are also considered along with pump power losses if a mechanical shift system is utilised for a multi speed transmission. Losses are typically based on ISO standard methods, supplemented by further techniques developed and validated in-house at Drive System Design.

An example of the calculated loss breakdown for a single operating point for two transmission architectures is shown in Figure 3. By extending these calculations to a range of speed and torques, operating efficiency maps can be created. A three stage parallel axis transmission is likely to be both more costly, and have more power loss than an two stage alternative as a result of the additional components and additional interactions. However, for a given total transmission ratio, a three stage transmission would require smaller individual mesh ratios, which is of benefit to power loss. Furthermore, higher total transmission ratios are possible in a three stage design, which in turn enables faster, and potential smaller motor options. Can the additional mass, cost and power loss in the transmission be offset and surpassed by savings elsewhere? Only a system approach as described will give indications as to where this is possible.

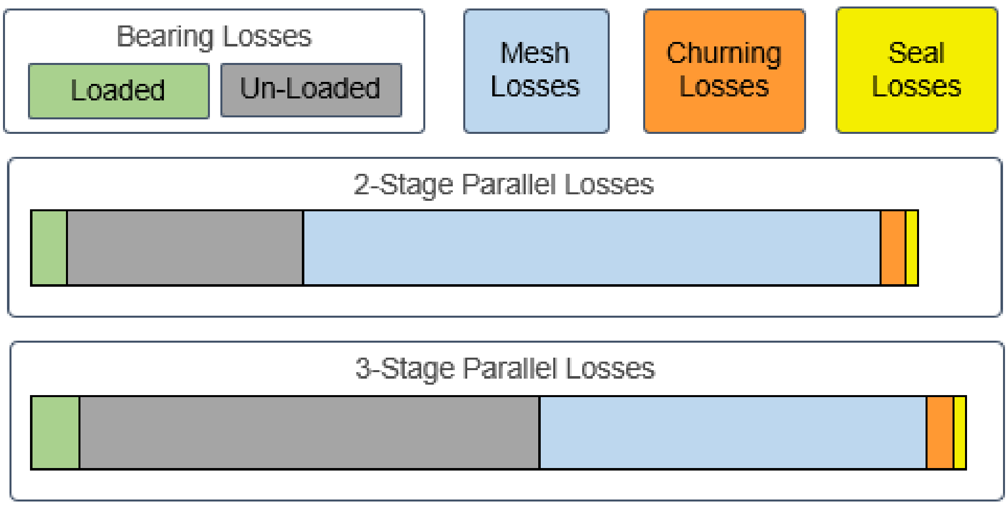

Figure 3: Example loss breakdown for two transmission architectures at 100 Nm / 1000 rpm input

3.2. Electric Motor Model

The electric motor models are generated through a subprogram developed in-house in Python, which calls Motor-CAD and automatically parameterises models to generate efficiency maps, material masses and inertias. The motor generation program is capable of generating a number of electric motor design types, utilising the appropriate Motor-CAD modules, including Permanent Magnet Synchronous Machines (PMSM) with multiple rotor topologies (surface mount and interior magnet (flat/U/V) with multiple layers), induction machines and switched reluctance machines as shown in Figure 4.

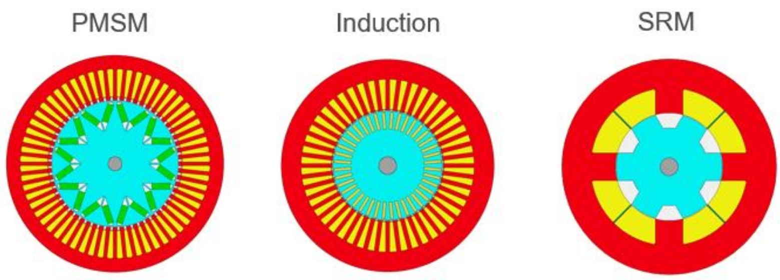

Figure 4: Examples of simulated motors

The program receives a topology demand along with a target peak and continuous power/torque, as well as further requirements such as Constant Power Speed Ratio (CPSR), maximum speed or a range of required torque or speed operating points. The program then selects the most suitable base geometry which meets the target power within thermal and structural limits, and iterates through a number of variables, including number of poles, magnet material, diameters and length, among others, to generate multiple designs that meet the required specification. A number of mechanical, manufacturing and electromagnetic constraints have been set to ensure each design is practical, such as rotor tip speed, length and diameter ratios, magnet and bridge thickness, current density, magnetic flux density, DC link voltage and back EMF at maximum speed. The material masses are exported from Motor-CAD and used to generate the total system mass, with motor geometry also contributing to the casing calculation. The cost of the motor is estimated from the raw material weights, and from considering manufacturing processes, in a similar manner as with the transmission.

An example of the losses for a PMSM and induction machine for a single operating point are shown in Figure 5, which in turn allow the generation of efficiency maps. It can be seen that on first impressions, a PMSM machine may be a likely decision, as it is likely to be more efficient. Both copper and iron losses are smaller, and despite the addition of magnet losses, these are sufficiently small such total losses are still less than the induction machine. What ePOP allows is the trade offs to be investigated. An induction machine could typically be expected to be cheaper than a PMSM, but without a complete system approach, it would be unclear as to whether this cheaper motor option would be offset by impacts on the system as a result. How efficient could an optimised induction machine based system be in comparison with an optimised PMSM based system, and does the difference in motor cost significantly impact total system cost?

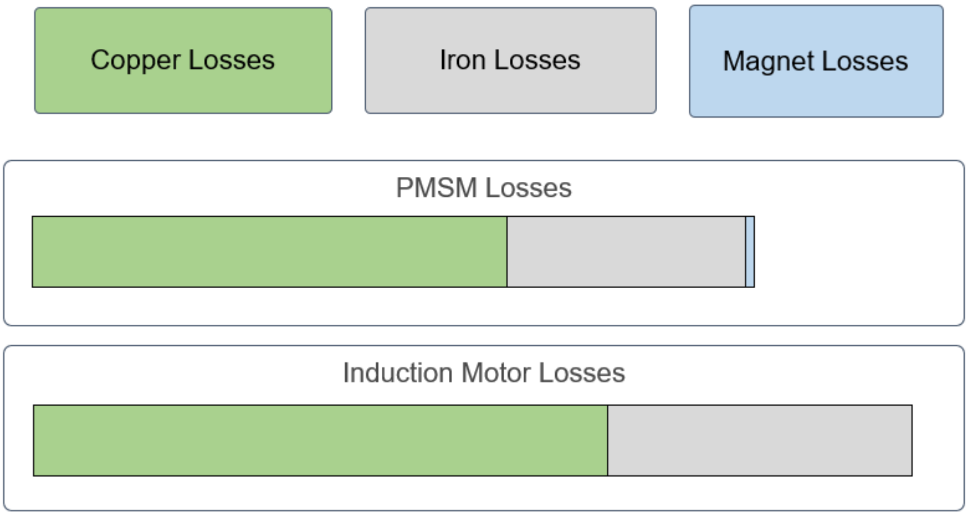

Figure 5: Example loss breakdown for two electric motor designs at 100 Nm / 1000 rpm input

3.3. Inverter Model

The two main inverter technologies currently in consideration are the conventional insulated-gate bipolar transistors (IGBT) and more recently available silicon carbide (SiC) metal-oxide-semiconductor field-effect transistors (MOSFETs). ePOP utilises a bespoke, DSD developed and validated inverter model that calculates the inverter efficiency map, mass and cost, all of which are required as inputs for the optimisation process. The inverter efficiency map is based on the inverter losses which comprise four main components; switching and conduction losses of the IGBT/MOSFET, turn-off losses, and conduction losses of the body diodes. These four losses are affected by the device temperature, gate driver resistance, motor power factor, current and DC linkage level, switching frequency and pulse width modulation (PWM) strategy. The inverter loss model incorporates all of these factors, characterising the inverter based on a known switch data sheet or future trends. The inverter cost and mass are based on the module technology and maximum voltage and current ratings.

An example of the losses for an IGBT and SiC inverter are shown in Figure 6. The SiC inverter can be seen to be more efficient than the more standard IGBT, by reducing gate losses, and eliminating diode switching losses. However, this benefit comes at an additional cost. This is an interesting trade off that ePOP allows the user to investigate: for a given application, when does a SiC inverter become a viable solution, and what can be done in the remainder of the powertrain to enable this decision?

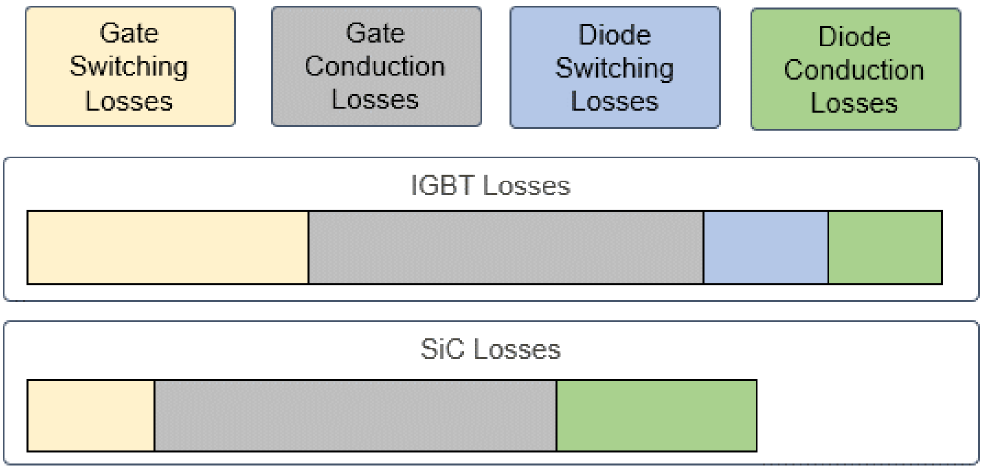

Figure 6: Example loss break down for IGBT and SiC inverter losses at a single operating point

4. Vehicle Model

The vehicle models are based in MATLAB/Simulink with a backwards-facing model being utilised for drive cycle simulation due to the computation efficiency, and a forward-facing model used for performance simulations (full-throttle acceleration tests). The backwards-facing vehicle model accounts for the vehicle inertia, rolling resistance, aerodynamic drag and gradient to calculate the torque required at the wheel and, through considering each components inertia and efficiency map, the energy required to carry out each drive cycle is calculated. The performance model can consider the first-order drivetrain dynamics and a tyre model.

The benefit of the vehicle model is that it allows subsystem performance to be directly related to vehicle targets, whether that's acceleration, top speed, or drive cycle efficiency. This extends the system approach further, allowing assessment and comparison of different systems across their operating conditions, rather than contrived load cases where one system may outperform another, in an unfair comparison. This allows the user to identify trends that result in quantifiable performance benefits, such as effects on 0-100 kph time, drive cycle energy usage, or vehicle range for a given battery size.

When simulating multi speed transmissions, an idealised approach is taken to allow the fairest comparison of powertrain architectures, avoiding the influence of pre-defined control strategies. As a result, the vehicle is allowed to operate in the optimal gear at each time during the cycle. The shift energy is calculated during post processing to account for all energy losses/regeneration, with shift efficiency taken into account.

5. System Cost

The cost function is primarily based on the bill of materials (BOM) cost of each powertrain subsystem which is accurately estimated for each subsystem architecture considered. Additional costs and weightings can be added based on exceeding or not meeting targets for weight and/or performance, or penalised as a result of associated NVH risk, or exceeding a given package volume or shape.

A key contributor to electric vehicle cost is the battery. Within the cost function, the process can adjust the battery capacity required to attain a defined target range through consideration of the change in system energy consumption over the drive cycle. This affects the total vehicle cost and enables the powertrain cost to be offset against the battery cost, allowing the user to accurately quantify the benefit of investing in the powertrain. An alternative to this approach would be to consider a fixed battery capacity and cost and evaluate the effect on vehicle range as an effect of powertrain decisions. Vehicle range is a key marketable attribute, as a perceived shortfall of electric vehicles, and a barrier to entry to many consumers.

6. Case Study

In this section an electric vehicle powertrain is optimised for a traditional and an autonomous vehicle, seeking to minimise powertrain cost for a given target range (vehicle parameters presented in Appendix 1). As discussed earlier, performance targets are key to optimising a powertrain and are presented in this section along with the modified drive cycle for an autonomous vehicle, over which the vehicle range is calculated.

Much research has been performed to propose how autonomous vehicles may be utilised. Karjanto *et al* [1] suggest that autonomous vehicles could be expected to perform in a similar way to light rail transit (LRT), with acceleration and deceleration rates within acceptable levels to allow passengers to eat and drink without risk of spillage, or work or play using electronic devices without discomfort. This is proposed to be equivalent to approximately 1.34 m/s^2 or 0.14g, in contrast to human driven cars which are typically between 0.25g and 0.50g, depending on driving style. As such, minimum wheel torque targets are more likely to be defined by drive cycle requirements, or gradeability, rather than 0-100 kph times or similar. However, gradeability targets may also be reduced for autonomous vehicles, which may be designed for specific and controlled conditions, with reduced focus on off road or all terrain capability.

This ignores further acceleration potential in traditional cars that is typically unutilised day to day as manufacturers deliver vehicles with short 0-100 kph times to appeal to performance driven customers. This highlights another potential benefit as a result of autonomous vehicles, the elimination of an unknown, the driver, in how the vehicle is used. As performance-based targets are replaced by those prioritising comfort, top speed requirements can be assumed to be limited to the highest legal limits (or to minimum limits where locally appropriate).

Potential performance targets for the autonomous and traditional vehicle are given below in Table 1.

Table 1: Potential performance targets for the autonomous and traditional vehicle

Parameter	Unit	Traditional	Autonomous
Vehicle Speed	[kph]	170	130
0-100 kph	[s]	10	20 (equivalent to ~0.14g)
Gradient	[%]	60	30

The traditional and autonomous vehicles were analysed for the same drive cycle, however, due to a smoother torque delivery by the autonomous vehicle, the speed profile was limited by the smoothing function presented by Liu *et al* [2]. A plot showing the velocity profile smoothed to represent autonomous vehicle driving alongside the original speed data is shown below in Figure 7.

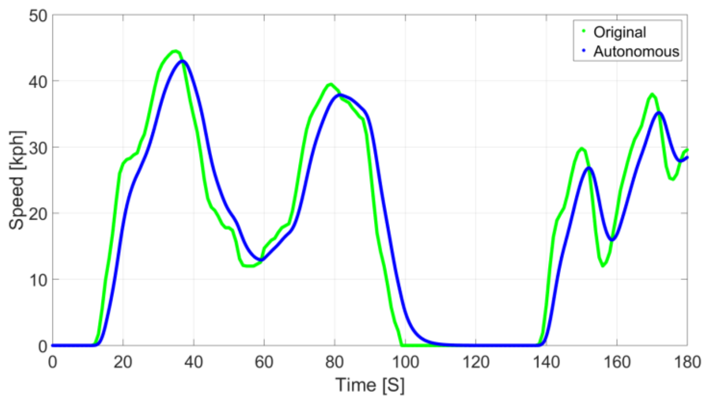

Figure 7: WLTC speed profile for traditional and autonomous vehicle

The altered drive cycle profile results in the electric motor time residency plots shown in Figure 8. The size and colour of the circles in each plot are proportional to the amount of time spent at the speed and torque condition. It can be seen that the peak torque that occurs over the drive cycle is reduced, and that the residency plot of the autonomous vehicle is more concentrated, spending more time at reduced torque conditions. This is a direct result of how the vehicle is used, with the smoothed velocity profile resulting in reduced acceleration and reduced torque requirements.

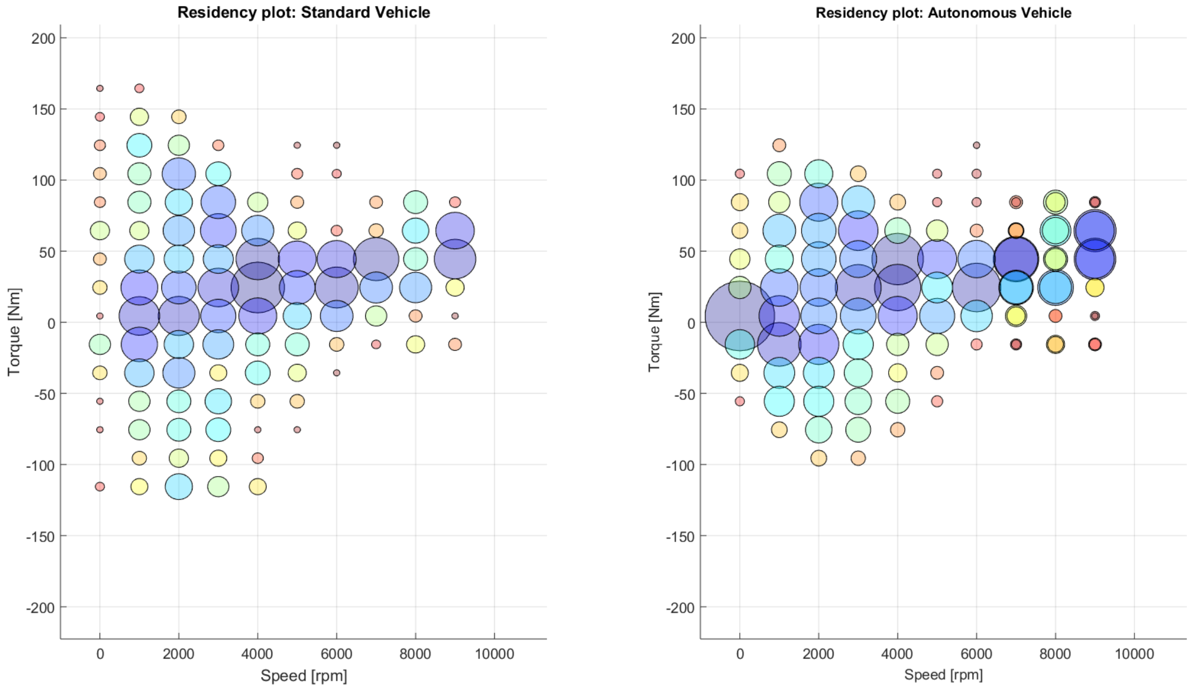

Figure 8: Electric motor time residency for traditional and autonomous vehicle over the WLTP drive cycle

The optimisation procedure was then run of a range of powertrain options, with variations in inverter, motor and transmission. The number of options used in the simulation was limited for presentation in this paper and run for a small set of permanent magnet motors with varying power, torque, CPSR and pole number, which were paired with either IGBT or SiC MOSFET inverters. The four transmission options used in the optimisation process are shown in Table 2.

Table 2: Transmission Architectures Analysed

Two-Stage Parallel Shaft
Three-Stage Parallel Shaft
Planetary into Single-Stage Parallel Shaft
Single-Stage Parallel Shaft into Planetary

7. Results

The traditional and autonomous vehicles were optimised over the Worldwide Harmonised Light Vehicle Test Cycle (WLTC) for every combination of electric powertrain that met the constraints set by the performance criteria. The resulting energy consumption and system cost for the autonomous vehicle are shown in Figure 9, where the huge number of possible powertrain types have been analysed.

The two distinct clusters in Figure 9 are due to the two inverter systems that have been analysed, the silicon carbide inverter forms the top cluster with an increased cost and reduced energy consumption due to the higher efficiency when compared to the IGBT results which form the lower cluster.

The motor efficiency maps are significant factors in the overall system efficiency maps, and so strongly affect energy consumption. In this case study, with limited variations and numbers of motors to analyse, the lower speed and thus lower ratio transmissions were favoured. This is due to the characteristics of the case study set of motors, which exhibited relatively low efficiencies at high speed.

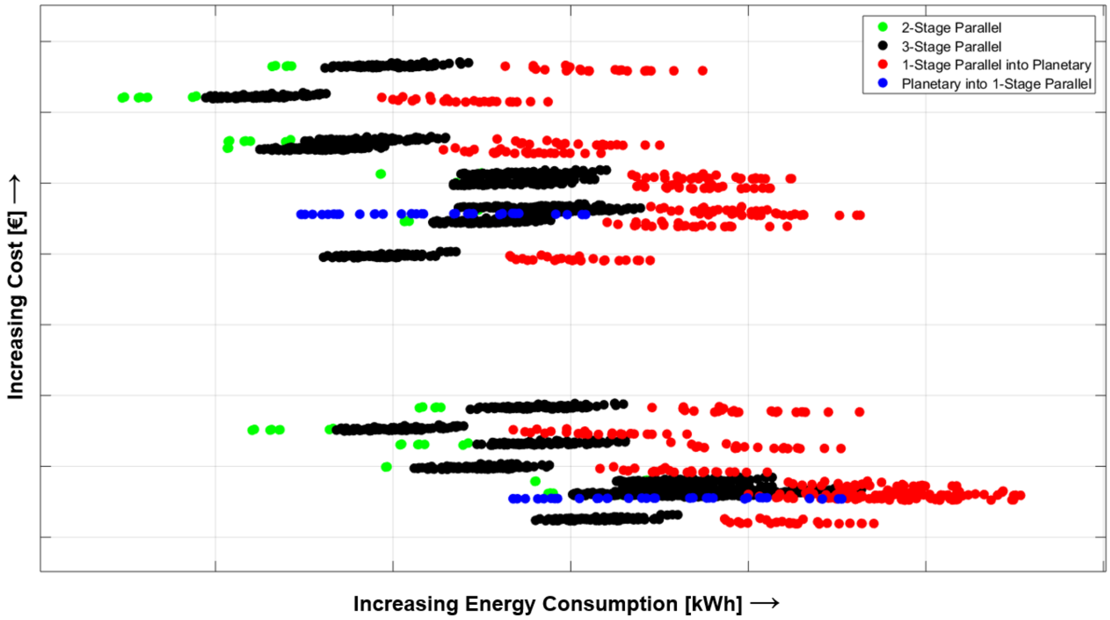

Figure 9: Energy consumption over WLTC v system cost for each powertrain simulated for the autonomous vehicle

The resulting optimal powertrains, in this case selected to maximise vehicle range, for the traditional and autonomous vehicles are shown in Table 3. The impact of the reduced performance requirements is evident in the motor selection, with both reduced motor power and reduced torque selected for the autonomous vehicle. Aside from this difference, many decisions remain consistent for both vehicle types. In both instances, a SiC MOSFET inverter has been chosen, due to the technology's reduced switching losses. The effect of inverter selection is more prominent at higher motor speeds where higher switching frequencies are required, resulting in larger efficiency gain from choosing a SiC MOSFET solution over IGBT. Similarly, for both the traditional and autonomous vehicle a 2-stage single-speed transmission has been chosen. This is in part due to the set of motors used in the study, where higher motor speeds have, in general, resulted in reduced efficiency over the drive cycle.

Table 3: Most efficient powertrain solutions for traditional and autonomous vehicle

		Traditional	**Autonomous**
Motor Type	[-]	IPM V (limited in this study)	
Motor Power	[kW]	140	110
Motor Torque	[Nm]	300	250
Inverter Type	[-]	SiC	SiC
Transmission Type	[-]	2-Stage Single-Speed	2-Stage Single-Speed

An alternative comparison has been made in Table 4, where the most efficient powertrain for the autonomous vehicle is compared with the lowest cost. To reduce the total cost of the system, a higher speed motor has been selected. This higher speed motor is smaller, with reduced magnet volume, and therefore reduced cost. To compliment this decision, a change in the transmission specification has occurred, changing from a 2-stage to 3-stage single speed, and a higher total ratio to suit the motor choice. However, an increased number of components, and an increase in transmission size result in a more costly transmission. In this example, the cost saving associated with the motor selection outweighs the additional costs from the transmission, resulting in an overall lower system cost. Finally, for the lowest cost option, the existing IGBT inverter technology has been adopted rather than the emerging SiC MOSFET, sacrificing the efficiency benefits associated with new technology to prioritise cost.

Table 4: Most efficient vs lowest cost powertrain solutions for autonomous vehicle

		Most Efficient	**Lowest Cost**
Motor Type	[-]	IPM V (limited in this study)	
Motor Power	[kW]	110	110
Motor Torque	[Nm]	250	200
Inverter Type	[-]	SiC	IGBT
Transmission Type	[-]	2-Stage Single-Speed	3-Stage Single-Speed

The next step is to consider the further implications of improved system efficiency. Improved efficiency means that, for a given battery capacity, a larger vehicle range could be achieved. Alternatively, for a given vehicle range, the capacity of the battery could be reduced. These options either result in a marketable selling point (i.e. promoting greater vehicle range against competitors) or further reductions in cost. Therefore, more efficient systems have further benefits to consider when the system approach is extended to consider the battery alongside the electrified powertrain.

8. Conclusion

The design and optimisation of electric powertrains remains, as a process, in its infancy, resulting in both challenges and opportunities. New technologies are being continually developed, but the cost of adoption in comparison with performance benefits are not always easy to quantify. The process and tools used by DSD aim to do so by considering a system approach, that allows subsystem model generation within itself, enabling concept generation to occur iteratively. Through characterisation of subsystem and component level behaviour, accurate system performance and costs can be predicted. This enables mapping of the potential design space, investigation of a wide range of complex interactions, and evaluation of new concepts at a system level.

The challenges and opportunities are only furthered when autonomous vehicles are considered. Use cases and requirements remain uncertain, however, it is generally agreed that performance related targets related to vehicle acceleration will likely reduce, as passenger comfort is prioritised. By removing the driver, vehicle manufacturers must embrace the opportunity to control how their products operate. By doing so, greater confidence in narrower operating conditions will allow significant optimisation potential over existing electrified powertrains, which must cater for more unknown behaviour. This is evident by the methods presented in this paper, whereby a smoother vehicle velocity profile results in reduced peak torque events and more concentrated motor operating conditions. This has enabled the selection of a smaller, lower torque motor, and associated cost savings.

The results presented in this paper are intended to be indicative of the potential that exists using this, or similar processes, and the particular benefits that are possible for autonomous vehicles. All electric vehicle powertrains should be designed using a system approach, that allows each major subsystem to be designed to work harmoniously with one another. The process outlined in this paper allows optimisation of the powertrain for a given application by considering the operating conditions of a given powertrain option over a given drive cycle. The major benefit of this process when considering autonomous vehicles is that these operating conditions can be better understood, and controlled, allowing further optimisation.

9. References

[1] Karjanto, J., Yusof, N.M., Terken, J., Delbressine, F., Hassan, M.Z. and Rauterberg, M., 2017. Simulating autonomous driving styles: Accelerations for three road profiles. In MATEC Web of Conferences (Vol. 90, p. 01005). EDP Sciences.

[2] Liu, J., Kockelman, K. M., Nichols, A., 'Anticipating the emissions impacts of smoother driving by connected and autonomous vehicles, using the MOVES model', January 2017, Conference: The 96th Annual Meeting of the Transportation Research Board.

10. Appendix

Parameter	Unit	Value
Mass	[kg]	2500
Wheel Radius	[m]	0.35
Cd	[-]	0.32
Frontal Area	[m^2]	3.5
Rolling Resistance Coefficient	[-]	0.013