

Model-Based System Optimization for Fuel Cell Hybrid Commercial Vehicles

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Summary

Model-based system optimization has been applied to find an optimal fuel cell powertrain system for three commercial vehicle types: commercial van, truck, and coach bus. System requirements for each vehicle are studied in terms of maximum performance, driving range, gradeability, and other performance targets. Two system architectures, namely hybrid and range-extender, and two fuel cell types—proton exchange membrane fuel cell (PEMFC) and solid oxide fuel cell (SOFC)—are considered. The best system architecture and fuel cell type are selected based on global optimization results that consider both hydrogen and fuel cell cost.

Keywords: fuel cell vehicle, PEM fuel cell, optimization, van, bus, truck

1 Introduction

The passenger vehicle sector has invested in zero emission technology due to environmental concerns and legislative pressure. The commercial vehicle sector, which emits disproportionately large amounts of CO₂, evidently also requires zero emission vehicle solutions. Notably, despite representing merely 4% of the European on-road vehicle fleet, heavy duty vehicles alone accounted for 27.4% of the on-road CO₂ emissions in 2015 [1]—and this share could rise to 37-41% in 2030 in part due to increasing freight activity [2].

Challenges for low-carbon commercial vehicles include long-distance travel requirements, minimal downtime for refueling, payload mass and volume constraints, limited technology availability and economies of scale. The lack of refueling or recharging infrastructure could be mitigated, because many applications are operated in limited regional areas or between specific hubs. Additionally, vehicle operators seek to minimize vehicle lifetime costs.

The two primary zero-emission commercial vehicle (ZECV) technologies are battery electric vehicles (BEV) and fuel cell electric vehicles (FCEV). FCEVs offer advantages over BEVs such as longer range and fast refueling owing to their high energy density. On the other hand, BEVs have merit in terms of lower operating costs and benefit from a more mature and lower cost charging infrastructure – especially compared to conventional hydrogen FCEV with a demanding requirement for handling, transporting and storing hydrogen. Other fuel cell alternatives such as solid oxide fuel cell (SOFC) or direct methanol fuel cell (DMFC) could, however, largely eliminate these issues.

Commercial vehicle requirements do not clearly favor either BEV or FCEV. Yet the industry has mainly focused on a binary choice between the two. Existing BEV solutions include electric buses and vans from OEMs including BYD, Volvo, Nissan, Renault, Citroen and Iveco, as well as BEV Heavy Goods Vehicles

(HGVs) following highly publicized announcements by Tesla and Daimler. HGV fuel cell vehicles are also currently developed by companies like Scania, Toyota and Nikola. There have, however been few public attempts combining the two technologies to maximize benefits of each in a single application. New types of FCEV – BEV hybrid powertrains could accelerate ZECV technology adoption by introducing new solutions that offer range, low operating costs, convenient refueling and zero emissions.

The aim of this research is to combine advantages of BEVs with those of FCEVs in order to compensate for disadvantages of either type in a commercial vehicle application. Two alternative powertrain concepts have been identified – a plug-in “fuel cell range-extender” (FCREx) and a non-plugin “fuel cell hybrid” electric vehicle (FCHEV). Two fuel cell types—proton exchange membrane fuel cells (PEMFC) and solid oxide fuel cells (SOFC) are considered for three different commercial vehicle types, namely vans, buses and trucks. This results in 12 different combinations that require individual optimization. The time required for properly developing such a high number of powertrains and control strategies is greatly reduced by utilizing advanced optimization in the form of dynamic programming (DP). The model-based system optimization is used by combining the usage of advanced optimization techniques with vehicle modeling and system boundary estimation based on system requirements.

2 Methodology

System engineering for hybrid powertrains is more challenging than that for conventional powertrains. This is because it involves a greater combination of systems and components, all which significantly impact the vehicle’s performance attributes. In order to find an optimal system and component selection, i.e. system optimization, model-based engineering, as adopted in this study provides a systematic quantitative framework [3]. Model-Based System Engineering (MBSE) is a brand of model-based engineering, which formalizes application of modelling to support system requirements, design, analysis, verification and validation from the conceptual design to production [4]. MBSE is especially useful at the beginning of product development as a model can replace hardware until a time when the actual hardware is available for the test.

MBSE has been used for hybrid vehicle system research as it is applicable to various system architectures and component sizes. Plug-in hybrid vehicles, for example, can have a selection of system architectures such as power split, output split and series output. Following MBSE, these architectures could be simulated and optimized using an optimization algorithm [5]. Hybrid system with one or two planetary gears as well as clutch elements is also an interesting subject for system optimization with modelling. Zhang [6] has studied power-split hybrid vehicles with a single planetary gear set by using MBSE to achieve best fuel economy, and L. Jinming [7] has researched two planetary gear split hybrid vehicles with similar approach. MBSE is necessary to find the best system architecture for two planetary gear split hybrid vehicle as there are more than thousand possible system architectures.

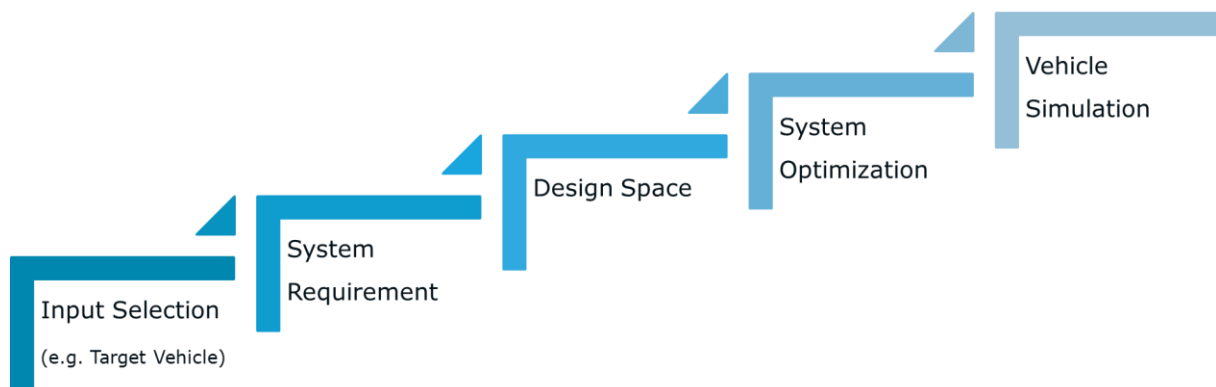


Figure 1: Model-based System Engineering

Fuel cell hybrid powertrain systems for commercial vehicles also require application of MBSE at the beginning of their development due to a wide range of system configurations and components range. In this study, the first step is selecting target vehicle since there are several variants of van, bus and truck. Here, the specific vehicle type is selected based on market share and fuel cell benefit. System requirements are defined

based on the assumption that the fuel cell vehicle would have similar vehicle requirements in terms of driving range, maximum acceleration, maximum speed, cost, and weight. Based on those requirements, a range of fuel cell and battery sizes is calculated in order to reduce computation time for system optimization. Once fuel cell type, hybrid architecture and components sizing are optimally selected, fuel consumption and acceleration performance are simulated in vehicle simulation model. A high-level step-wise description of the overall MBSE design process is shown in Fig. 1. The rest of the paper describes the depicted steps in greater detail.

3 Input Selection

One of the challenges of commercial vehicles selection is the plethora of variants. In order to meet different customer needs sub-categories exist for each vehicle type, which often requires different powertrain specifications. For example, a delivery van it is categorized by vehicle weight and highest weight class. In this study, delivery van class N1-is selected based on its sale in the UK [8]. For coach bus and truck, not only sales but also fuel cell technology benefit are considered. To explain why, a city bus, for example, is expected to have less benefit with fuel cell compared to BEV technology since it requires short driving range per charge and therefore the limited battery range is not an issue. A Coach bus, on the other hand, requires longer driving range and therefore frequent battery charging could be problematic. For the truck, the same rationale as with the coach bus is applied and a long-distance truck with 3-axle semi-trailer is selected.

In this study, two different fuel types are considered: the proton exchange membrane fuel cell (PEMFC) and solid oxide fuel cell (SOFC). While the PEMFC is widely used for automotive applications in the market due to its high efficiency and technology maturity, the SOFC has an advantage of high energy density with different input energy sources. The SOFC is considered over a Direct Methanol Fuel Cell (DMFC) because it has a higher efficiency and can be used with diesel, a commonly available fuel for commercial vehicles (see Table 1). Therefore, the SOFC requires less infrastructure investment for commercial vehicles since conventional trucks and buses have easy access to a diesel fuel station. The main disadvantage of the SOFC is its high operating temperature and consequently longer warm-up time, which are both taken into account in system optimization. Additionally, ethanol is considered for SOFC instead of diesel due to its high efficiency and low greenhouse gases.

Table1: Fuel Cell Comparison

	PEMFC	SOFC	DMFC
Electrolyte	Polymer membrane	Solid oxide or Ceramic	Polymer membrane
Fuel	Hydrogen	Hydrogen, Diesel, Gasoline, Ethanol, Methanol etc.	Methanol
Efficiency	45-65%	40-50% (with Ethanol) 30-40% (with diesel)	20-30%
Operating Temperature	65-90 °C	500-1000 °C	90-120 °C
Pros	High power density	High energy density, No metal catalyst, Tolerant to CO poisoning	High energy density
Cons	Sensitive to fuel impurities Expensive platinum catalyst	Longer warm-up time	Low power density
Application	Automotive / Mobile	Stationary application	Mid-sized application (e.g. mobile & laptop)

Fuel cell powertrain systems can be categorized as full fuel cell hybrid and fuel cell range-extender vehicle based on the power ratio of battery to fuel cell and the existence of external charging system (see Fig. 2). Fuel cell hybrid vehicles are not new in the passenger fuel cell vehicle market. Notable examples are the Toyota Mirai and Hyundai NEXO, where a small capacity battery is used mainly to capture regeneration

energy, support EV mode, and to assist when fuel cell efficiency is low. Fuel cell range extender vehicles on the other hand have a large battery capacity, which can provide enough EV range such that when state of charge (SOC) of battery is low, the fuel cell can provide power to propel the vehicle and to charge the battery at the same time. Such a range-extender fuel cell van has been developed by Renault [9].

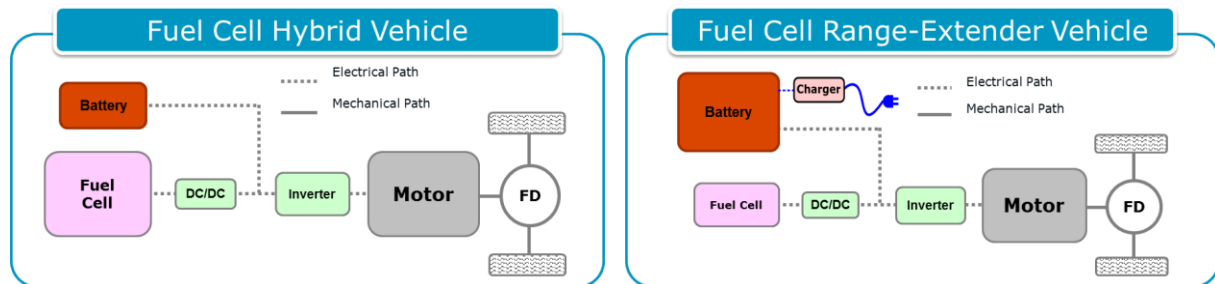


Figure 2: Fuel Cell Vehicle System

4 System Requirements

To select an optimal powertrain system architecture and fuel cell type, and to define the best combination of battery and fuel cell, system requirements need to first be defined for each vehicle application. System requirement specification is especially critical for commercial vehicle applications since requirements may vary depending on vehicle type and usage. For the three commercial vehicle types selected in the previous section, the requirements differ in target driving cycle and target performance attributes.

Regarding the target driving cycle, a homologation cycle is used for system optimization and vehicle simulation. For a van, the Worldwide harmonized Light vehicle Test Cycle (WLTC) is used. For coach bus and truck, homologation cycles from the Vehicle Energy Consumption calculation Tool (VECTO) are used [10]. Figure 3 describes the cycles used for the van, coach bus and truck.

Item	Van	Bus	Truck
Driving Cycle	WLTC	VECTO Coach Cycle	VECTO Long-haul Cycle
Description	<ul style="list-style-type: none"> Used for homologation of van < 3.5 tons Time-based speed profile No gradient 	<ul style="list-style-type: none"> Used for homologation of Coach bus Distance-based speed profile With gradient 	<ul style="list-style-type: none"> Used for homologation of Truck Distance-based speed profile With gradient
Total Distance	23 km	275 km	100 km
Profile			

Figure 3: Target Driving Cycle

Regarding performance targets, it is assumed that fuel cell vehicle should provide similar performance as a conventional powertrain vehicle. Key target performance data is collected in Table 2; specifically, distance-to-empty, maximum vehicle speed, 0-100km/h acceleration time and gradeability. It is important to estimate fuel cell vehicle weight since it makes an impact on vehicle performance. By using weight data of fuel cell, battery and hydrogen tank, fuel cell vehicle weight is calculated starting from the conventional vehicle weight. As cost is also an important aspect in system selection, component cost projection for 2020 is used to estimate fuel cell vehicle cost.

Table2: Performance Target

Attribute	Units	Delivery Van	Coach Bus	Truck
Distance-to-Empty	[km]	400	700	1000
Maximum Speed	[km/h]	150	110	100
0-100km/h Acceleration	[sec]	12	30	14
Gradeability	[%]	30	25	25

5 Model-Based System Optimization

The purpose of system optimization is to find the best combination of components that provide a cost-effective solution for a given component set and constraints. It is a time-consuming process running the simulation for each and every component size variation for a given vehicle. The search is therefore automated following a model-based approach. The first step of system optimization in this study is to define a design space to check fuel cell and battery power/size range meeting the performance targets. Then, to compute fuel consumption, a control strategy is required. It is not possible to design and optimize a real-time control strategy for each combination. Dynamic Programming (DP) is used to estimate optimal fuel consumption since it guarantees an optimal control strategy for a given drive cycle. Based on fuel consumption, fuel cell vehicle running cost (i.e. fuel cost in dollars) is estimated, and powertrain cost can also be estimated with predicted powertrain component cost in 2020. Optimal system, fuel cell type and component size is selected for each vehicle type based on total cost from running cost and powertrain cost.

5.1 Design Space

A design space is calculated before system optimization in order to reduce computation effort for dynamic programming. Reducing design space upfront enables more effective use of computation time – eliminating infeasible component combinations in advance and therefore unnecessary DP optimization at these combinations. At the beginning, a minimum and maximum of battery and fuel cell size [i.e. maximum power] are selected. System requirements are then defined as described in Section 4, with cost, weight and volume considered to narrow the design space.

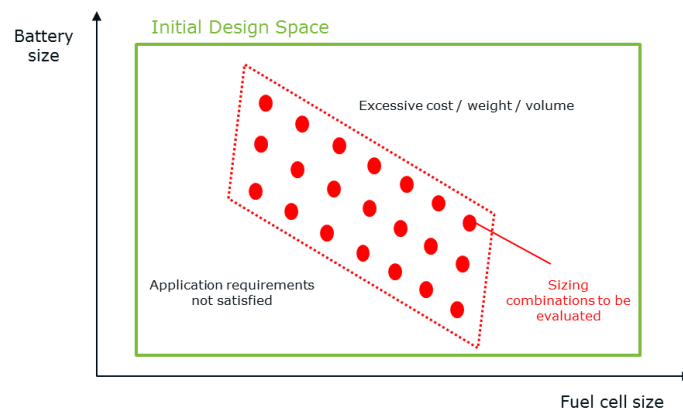


Figure 4: Design Space

Evaluation of vehicle performance in terms of maximum speed, acceleration and gradeability is conducted by using a simple vehicle model, which defined the lower boundary of design space. The other criteria to be considered are powertrain cost, weight and volume, all which are related to component size. Indeed, cost, weight and volume limit the upper boundary of design space (see Fig. 4).

5.2 Dynamic Programming

Dynamic Programming is used to find an optimal control strategy in terms of component power and to obtain best fuel consumption. For system engineering of hybrid powertrains DP is widely used in order to find best system architecture and components size [6, 7]. Although there are other optimization algorithms such as Pontryagin's minimum principle (PMP) and convex programming, DP is chosen as it guarantees global optimal solution and provides flexibility to take into account additional attributes like component degradation.

DP is a powerful tool to compute global optimal solution based on Bellman's optimality principle [10]. Bellman has proposed a method to transform the complex problem to a series of sub-problems. A discrete-time vehicle model can be described as in Eq. (1):

$$x(k+1) = f(x(k), u(k)) \quad (1)$$

where, $x(k)$ is the state vehicle of the system and $u(k)$ is the control vector. For fuel cell hybrid system, $x(k)$ is battery SOC and $u(k)$ is power split ratio between battery and fuel cell.

A cost function to be minimised must be defined. Whereas for conventional hybrid vehicles the cost function is normally fuel consumption, hydrogen consumption constitutes the cost function for fuel cell hybrid vehicles. To calculate hydrogen consumption, a backward-facing vehicle model is used as described in Eq. (2)

$$P_{Mot} = P_{Bat} + P_{FC} \quad (2)$$

Where, P_{Mot} is motor power demand, P_{Bat} is battery power, P_{FC} is fuel cell power. Motor power demand can be calculated with known vehicle specifications and known vehicle speed.

The optimal solution can be calculated by finding minimum of cost function based on Bellman's optimality principle. In general, the following minimisation problem is solved

$$J_{n-1}^* = \min_{u(N-1)} [L(x(N-1), u(N-1))] \quad (3)$$

where, L is cost function defined for given problem. It is solved backward from $N-1$ to 0 with vehicle model and cost function defined.

5.3 System Optimization

The goal of system optimization is to identify fuel cell system architecture and component sizing, which can provide minimum total cost combining powertrain and operating cost while meeting system performance requirements. Based on optimal fuel consumption calculated with DP, vehicle operating cost can be obtained combining with assuming annual mileage as shown in Eq. (4)

$$\text{Annual Running Cost [USD]} = \text{Fuel Consumption} \left[\frac{kg}{km} \right] \times \text{Annual Mileage [km]} \times \text{Fuel Cost} \left(\frac{USD}{kg} \right) \quad (4)$$

In DP it is important to set a final SOC, especially for the range-extender hybrid since this vehicle can have significant pure electric driving range, or charging depleting (CD) mode. In order to take into account charging depleting distance ratio over total trip distance, European Commission defines Utility Factor (UF) based on real world data analysis [12]. The UF of a specific vehicle depends on the charging depleting range and different vehicle type like bus and truck, needs different UF factor. Since UF for bus and truck is not defined yet in this study UF of Van is scaled based on annual mileage.

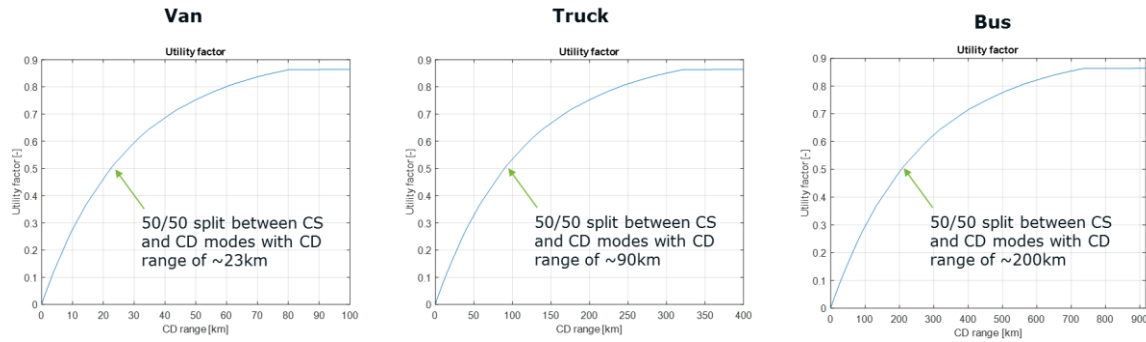


Figure 5: Utility Factor (UF)

From DP, fuel consumption of charging sustaining (CS) mode can be calculated. Figure 5 shows hydrogen fuel consumption results for Van with discrete design space defined in Section 5.1. In terms of battery size the smaller battery the less regeneration energy and consequently fuel consumption is degrading. As battery size increased fuel consumption improves until battery weigh deteriorate fuel consumption more than regeneration benefit. In terms of fuel cell size optimal power for Van is fairly low as request wheel power of WLTP is small. However, decreasing fuel cell beyond a certain point starts to degrade fuel consumption. This is because operating fuel cell at high efficiency area requires charging and discharging battery. Bus and truck show similar trend as van.

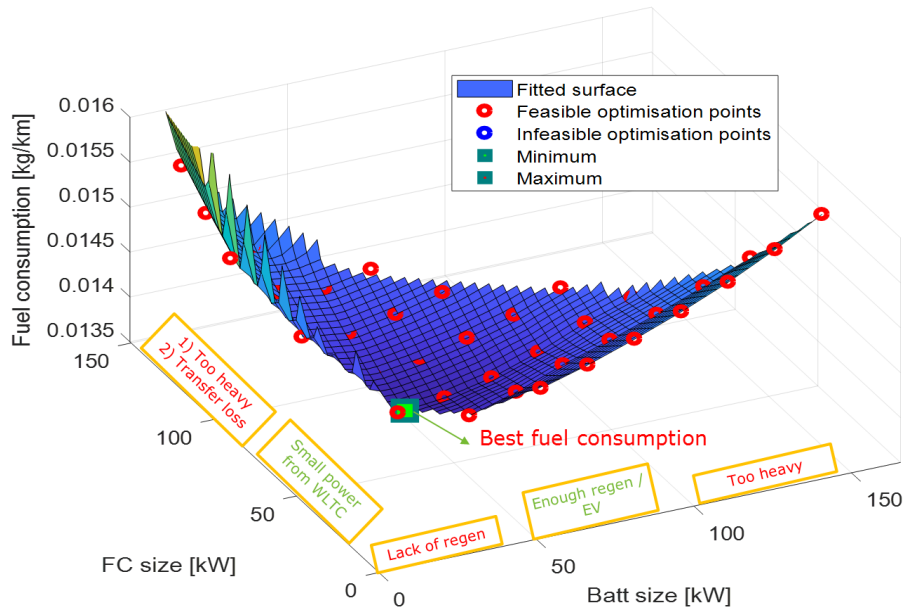


Figure 6: DP Results for Van

From fuel consumption of DP vehicle running cost can be calculated and powertrain cost can be obtained with components cost depending on component sizing. Total cost is summation of running cost and powertrain cost and is dominated by powertrain cost since fuel consumption differences are relatively small and its mileage is not long enough to make up for higher powertrain cost.

Table3: Cost Results of Van PEMFC

Item	Value	Comments
Operating Cost	\$ 20k - 24k	Assumption: 30,000 km/year, 10 year operation
Powertrain Cost	\$ 24k - 47k	Based on components cost defined for 2020
Total Cost	\$ 39k - 60k	Operating cost + Powertrain cost

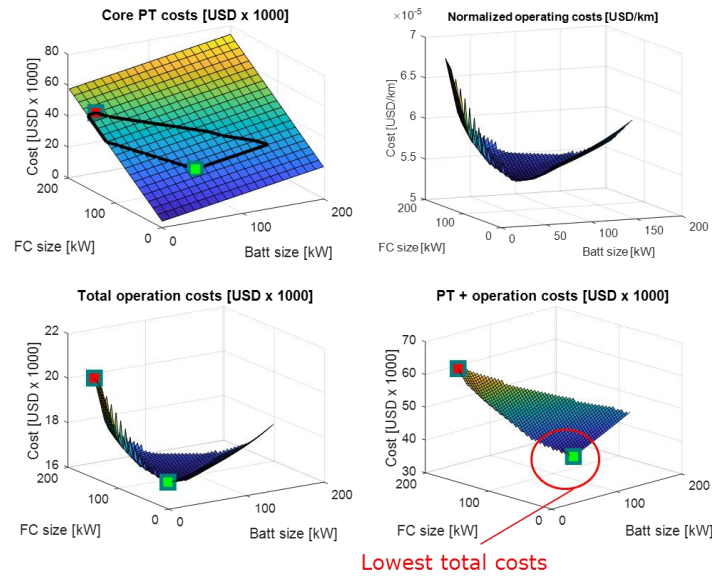


Figure 5: System Optimization Results for Van PEMFC

The same process is repeated for different fuel cell types, vehicles, and powertrain system types. The range-extender system is commonly selected since it can provide longer EV driving range, which allow the owner to save fuel consumption. With regards to fuel cell type PEMFC is selected for van and bus owing to its higher efficiency compared to the SOFC, while SOFC is selected for truck as its weight could be smaller due to high energy density of diesel compared to hydrogen, which is dominant to truck.

Table 4: System Optimization Results

Item	Van	Bus	Truck
System	Range-Extender	Range-Extender	Ranger-Extender
Fuel Cell Type	PEMFC	PEMFC	SOFC
Fuel Cell Power	17 kW	160 kW	115 kW
Battery Power	98 kW	400 kW	320 kW
Total Cost (10 yrs)	25,870	731,300	392,200

6 Vehicle Simulation

The final vehicle selection in Table 3 is now simulated with a driver model in a forward-facing simulator to assess fuel consumption. For such a simulator, DP energy management is inapplicable; therefore, a real-time implementable control strategy for the vehicles' energy management system (EMS) must first be developed.

A rule-based EMS is adopted here owing to its low computational demand and simplicity. The following sections describe the development of the adopted rule-based EMS and subsequent vehicle simulation results.

6.1 Rule-Based Energy Management

By examining the fuel cell power profiles generated with DP in a backward facing simulation (see Fig. 6), it is generally observed that the fuel cell supplies either a steady power or no power. This is because fuel cell efficiency is constant depending on fuel cell power. This observation leads to the creation of the following main rule for the EMS: when the fuel cell is active, a constant power request from the fuel cell is to be made.

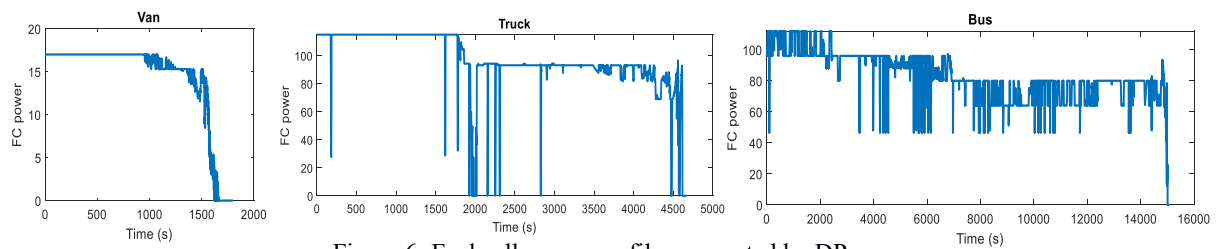


Figure 6: Fuel cell power profiles generated by DP.

The actual requested fuel cell power is set depending on the battery's state of charge (SOC) and is defined by the SOC modes depicted in Fig. 7. When battery is fully-charged battery energy is used at first unless the request power is above battery maximum power like full acceleration. When SOC is reached the certain level it enters charging sustaining (CS) mode, which mean the vehicle operates like hybrid vehicle to sustain SOC while seeking higher system efficiency. If SOC is dropping due to high demand power or high auxiliary power SOC mode switches to CS Low. In this mode the vehicle is considering system efficiency but battery charging is high priority. If SOC is dropping further, battery charging is high priority over vehicle performance by limiting request power or air conditioning power.

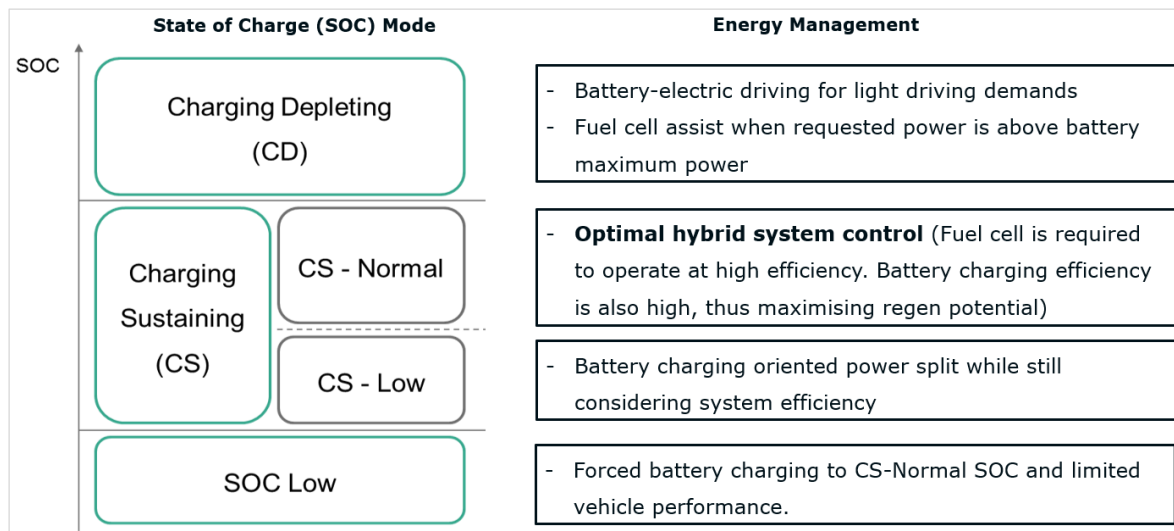


Figure 7: SOC Modes and Energy Management.

6.2 Simulation Results

After creating energy management strategy and plant model, the simulation is conducted to assess fuel consumption benefit. As baseline and fuel cell hybrid vehicle are using different input energy source it is necessary to convert fuel consumption to same metrics like well-to-wheels CO₂ and annual running cost. The well-to-wheel analysis is subject to how to generate hydrogen and in the UK it is mainly coming from steam methane reforming at the moment [13, 14]. In the future, if hydrogen can be produced from renewable energy, its CO₂ emission would be reduced dramatically. For annual running cost, the price of hydrogen is assumed at \$3.96/kg (projected price for the year 2020 [15]), while that of diesel is assumed at \$1.75/L, and ethanol at \$2.25/L [16]. The annual mileage of the vehicles is 30,000 km for the van, 275,000 km for the bus and 120,000 km for the truck. Simulation results and baseline comparison for the van, coach bus and truck are provided in Table 5.

The simulation results show that annual fuel cost and well-to-wheels CO₂ emissions for a fuel cell hybrid of van and bus is better than that for its conventional vehicle counterpart. When hydrogen price reaches to \$3.96/kg in 2020, an owner could save \$1,770 and \$81,376 every year for van and bus respectively. In terms of well-to-wheels CO₂ emission, fuel cell hybrid vehicle provides 10% and 18% improvement for van and bus respectively. For truck, even though fuel consumption of fuel cell is better than that of baseline, its running cost is equivalent due to its higher ethanol cost. Its well-to-wheels CO₂ emissions, however, is much lower than baseline as ethanol produces less CO₂ while producing it.

Table 5: Simulation Results

Item	Van (WLTC)		Bus (VECTO Coach)		Truck (VECTO Long-haul)	
	Baseline	Fuel Cell Hybrid	Baseline	Fuel Cell Hybrid	Baseline	Fuel Cell Hybrid
Fuel consumption	7.32 L/100 km (Diesel)	1.74 kg/100 km (Hydrogen)	33.5 L/100 km (Diesel)	7.33 kg/100 km (Hydrogen)	31.3 L/100 km (Diesel)	24.6 L/100 km (Ethanol)
Well-to-Wheels	238 CO ₂ e g/km	214 CO ₂ e g/km	1088 CO ₂ e g/km	903 CO ₂ e g/km	1,017 CO ₂ e g/km	168 CO ₂ e g/km
Annual running cost	\$3,840	\$2,070	\$161,200	\$79,824	\$65,750	\$66,310
Engine / Fuel cell	2.2 L / 114 kW	17 kW PEMFC	12.8 L / 317 kW	160 kW PEMFC	12.5 L / 317 kW	115 kW SOFC
Battery	N/A	98 kW	N/A	400 kW	N/A	320 kW
Transmission	6-speed manual	Single-step Gearbox	12-speed AMT	Single-step Gearbox	12-speed AMT	Single-step Gearbox
Final drive ratio	4.19	8.60	3.58	13.00	2.80	14.50
Test weight	2,270 kg	2,349 kg	17,028 kg	17,838 kg	27,400 kg	27,400 kg

7 Conclusion

Model-based system optimization for commercial fuel cell vehicles is proposed and applied to three different vehicle types: van, coach bus and truck. For a vehicle with multiple energy sources, the optimal energy management strategy depends on sizing of the powertrain components. Fair comparison of the fuel consumption of different sizing of powertrain components requires modifying the control strategy for each sizing. Adjusting the control strategy manually for all the combination of components sizing requires tremendous amount of time and effort. In this study it is automated to compute optimal fuel consumption with a global optimization algorithm, dynamic programming.

Based on literature review and market research for conventional commercial vehicles, a target conventional vehicle's attributes are matched to those of the fuel cell vehicle counterpart. A design space is then calculated before running the DP algorithm in order to reduce computation time. Within the design space, a discrete combination of battery and fuel cell component sizes is used. The DP algorithm is then run to obtain optimal fuel consumption and a running cost (in currency US dollar) in the end. Powertrain cost is also estimated based on component information searched from literature or market information. After combining operating cost and powertrain cost, the powertrain combination with minimum total cost is selected.

Range extender hybrid system can provide more benefit than hybrid vehicle as its pure electric driving range has better efficiency and low running than hybrid mode. Two charging for range extender hybrid system could be problematic due to longer charging time of both hydrogen and electricity. In terms of fuel cell type PEMFC is better for van and bus but SOFC is selected for truck.

Fuel consumption of baseline and fuel cell hybrid vehicle are compared in terms of annual running cost and well-to-wheels CO₂. For van and bus, annual running cost of fuel cell is almost half of that of baseline and well-to-wheels CO₂ of fuel cell has improved approximately 10% and 20% respectively. For truck annual running cost of fuel cell is as similar as that of baseline but well-to-wheels has improved significantly as the process of generating ethanol emits less CO₂ than that of hydrogen.

In conclusions, the model-based system optimization is proposed and applied to find a best fuel cell system for a commercial vehicle application. This method is applicable to other system engineering for powertrain system.

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Tom Kigezi is a CAE engineer for electrification in the CAE & Data Science Team at AVL, having started in 2018. He has a background in Control Engineering within the automotive sector and has taken on both industry and research responsibilities largely focusing on hybrid vehicle development. He holds a Masters degree in Control Systems Engineering



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