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Metamodelling-based Product Family Design of Plug-in Hybrid Electric Vehicles

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ABSTRACT
Development of plug-in hybrid electric vehicles (PHEVs) is stimulated by the need to replace non-renewable energies with sustainable and more environment-friendly new energy types. PHEVs benefit from a combination of an internal combustion engine and an electric motor with a rechargeable and larger battery pack than conventional hybrid vehicles. In order to maximise customer satisfaction and motivate replacement of the conventional vehicles with this new technology, the design of PHEVs requires sufficient differentiation in the product specifications for diverse market segments. The added set-up time, processes, costs and longer lead time for designing and manufacturing a diverse range of such vehicles is a hurdle towards increasing their diversity. This study proposes an efficient product family design (PFD) method for mass customisation of the PHEV powertrains. The methodology is less dependent on expensive simulations due to use of metamodelling and non-conventional sensitivity analysis. The PFD concept and its implications to a family of five PHEVs are investigated, and benefits as well as limitations of a sustainable development for this complex product are discussed.

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PHEV design; product family design; engineering design for sustainable development; simulation-based design Optimisation; high-dimensional expensive black-box (HEB)

1. Introduction

The transportation sector has become the largest consumer of the oil resources in recent decades, absorbing around 49% of such energy resources, and the estimations show that if the current trend continues, all such resources will be depleted by 2038, according to Amjad, Neelakrishnan and Rudramoorthy (2010). Accordingly, since a few decades ago, the need for reduction of the emissions to control air pollution and global warming, as well as the importance of reduction in the dependency on oil has directed the attention of developed countries towards technology advancement for vehicles. The plug-in hybrid electric vehicles (PHEVs) benefit from a combination of an internal combustion engine (ICE) and an electric motor with a rechargeable and larger battery pack than conventional hybrid vehicles. PHEVs are differentiated from hybrid electric vehicles (HEVs) based on the mileage that they can drive in the electric mode without using any fuel (referred to as all electric range, AER). $PHEV_x$ is a widely known way of characterising these vehicles, where x shows the range that the vehicle can drive purely on battery power (Shiau and Michalek 2009).

While AER can be one of the design factors, other performance requirements can be of equal importance, including the acceleration time, maximum speed and gradeability. As such, the combination of three component sizes including the ICE, battery and electric motor – together known as the powertrain – is of remarkable importance in PHEV design. Another important factor is the defined strategy to leverage the propulsion resources, which is referred to as the control strategy.

While variety in the design can increase the marketability of any given product and attract more market segments, it can in turn result in increased effort and cost for manufacturing them. Therefore, for a complex product like PHEVs, product family design (PFD) can be an efficient solution to meet both targets (i.e. satisfying more customers, and obtaining manufacturing efficiency).

PFD is a strategy to increase the manufacturing cost savings through commonalizing components/variables or functions in different products, and increasing the product diversity for larger share of the market. Product family is a group of related products – known as variants – which are differentiated from a set of common components, modules, functions or sub-systems – known as platforms. PFD can be challenging due to the increased complexity from identification of the best components to be shared among variants, and the best values for each of those components without sacrificing the performance of individual variants (Simpson, Maier, and Mistree 2001).

The phase of determining the best variables to be in the platform, and the best variants to be included in each platform/sub-platform is referred to as platform configuration. The aim at a platform configuration problem is to solve the platform and the entire family design problem in a way that results in losing as little as possible on the performance of individuals, and helps obtaining as much as possible on commonality (Pirmoradi, Hajikolaei, and Wang 2014). The platform and the individual variants should be selected such that the individual performance targets are not compromised, or will be of the least allowable performance loss Khire, Messac, and Simpson (2006).

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Family design problems can be scale-based, module-based or generational. Scale-based families include variants that all possess the same variables or functions, and some of the variables can take common values, while other variables have unique values in each variant. The module-based family includes variants that share some functions, while each variant has some unique functions or modules. In this study, a scale-based family design methodology is proposed which is previously applied to a widely known test problem in the PFD area, and based on the promising results on its efficiency, it is applied for designing a family of five power-split PHEVs (Pirmoradi, Hajikolaei, and Wang 2015).

PFD is discussed to be one of the strategies towards sustainable design, in that it entails into re-usability and design of mechanisms for efficient redesign of current generations, as well as design of future generations of a given product Kasarda et al. (2007). Scalability is also a means of reducing the overhead costs in design, and several other cost components such as inventory cost, supply chain and replenishment costs, manufacturing set-up cost, product maintenance and customer service costs, and therefore, is in line with the concept of sustainable design.

The rest of the paper is structured as follows: a literature review section is provided first to address the developments in the PFD area along with theory and achievements in PHEVs design and optimisation; the proposed method section provides the theory behind and the detailed steps of the PFD method developed in this study; then a discussion is provided on verification of the effectiveness of this methodology. Finally, conclusion is drawn based on the obtained results. Limitations of this study will also be discussed.

2. Literature review

PHEVs benefit from an electric drivetrain and internal combustion drivetrain that can be coupled to each other. These drivetrains allow the energy paths to the road to be in parallel, in series or in a combination (Bradley and Frank 2009). While the conventional ICE-powered vehicles might be more effective in higher engine loads, since they are usually operated at lower loads, they do not have impressive overall efficiency as reported by Heywood (1988). Although the pure electric vehicles (EV) can be of the highest benefits in terms of fuel replacement and green house gas (GHG) emissions elimination, they have limited ability for long driving ranges and the battery technology needs remarkable improvement to enhance their functionality.

The PHEVs can use electric energy over longer distances as compared to HEVs, which comes from the electric outlet connection feature embedded in their design. Use of larger battery packs helps meeting this target and provides the possibility of charging the battery overnight or off the peak hours.

PHEVs can take one of three forms in configuration of their powertrain: series, parallel and power-split configuration. The series configuration for an HEV/PHEV is equivalent to having an EV with an extended electric range. This configuration decouples the engine from the wheels so that the engine can be operating independently to charge the battery with the help of the generator. The motor supplies the power to the wheels and it takes its power from the battery. In parallel configuration, the power is added from the engine to the wheels, and engine and motor are both directly connected to the wheel and the vehicle is propelled by both simultaneously (Turlapati 2010). The engine is not connected to the generator, but is coupled directly to the transmission. The power-split configuration allows for operation in both series and parallel configurations. In this configuration, the power split depends on the power-split device (PSD), referred to as planetary gear set. The advantage of this configuration is that in this configuration the engine speed is decoupled from the vehicle speed, and therefore the engine can be operated at maximum efficiency (Turlapati 2010).

The trade-off among these configurations can be quite complex to balance the efficiency, cost, manufacturability and drive-ability, and there is no globally optimal configuration when all criteria are considered. However, for any chosen configuration, PHEVs can be constructed through optimizing the component sizes according to Johnston et al. (1998).

The power management strategy is the algorithm that determines the split of power request between the combustion engine and electric drive. It is a vital factor for the efficiency of a PHEV, as different control strategies result in different performance profiles due to the different basis of choosing operation modes. The operation modes of a PHEV include the charge-depleting (CD) mode in which the battery is the only source of propulsion, and the charge-sustaining (CS) mode where the engine is leveraged as an auxiliary power source for keeping the battery state of charge (SOC) remaining within a specific range. In this case, PHEVs operate similar to HEVs according to Nemry, Leduc, and Munoz (2009). There are several types of control strategy, each imposing specific restrictions on the propulsion sources to run the vehicle (Graham 2001).

The product platform concept exploration method (PPCEM) by Simpson, Maier, and Mistree (2001), is among the early developments in this area, leveraging robust design principles to minimise the performance sensitivity to the variation of the scale factors. Fixed platform variables have been assumed by Messac, Martinez and Simpson (2002a), where PPCEM and physical programming have been aggregated for PFD. Another PFD development is by Fellini et al. (2005), where commonality is treated as a constraint in the design problem. Unknown platform architecture involves the task of platform configuration as well, and Nayak et al. integrated this task with the commonality–performance trade-off problem, known as the variation-based platform design methodology (VBPDM), developed by Nayak, Chen, and Simpson (2002). VBPDM attempts to maximise commonality within the family while achieving the performance requirements by varying the smallest number of design variables. The product family penalty (PFPF) function is another method developed by Messac, Martinez and Simpson (2002b) to find the best set of platform and scale variables for minimum performance losses of commonalisation.

The concept of sensitivity analysis for PFD was first used by Fellini et al. (2004) where the performance losses resulting from sharing were measured through sensitivity analysis for identifying the proper candidates as scale variables. This study uses the sensitivity analysis-based method developed in Pirmoradi, Hajikolaei, and Wang (2014) for family design of simulation-based problems that might be challenging due to the large number of function calls. The proposed method uses a metamodel-based analysis approach. Metamodelling is a technique which enables creating reliable surrogate models or mathematical representation for describing the relationship between input and output of unknown systems. Such systems are known as expensive black-box problems, and the metamodelling technique not only can reveal the unknown behaviour that transforms the input into the output, but also can provide useful information about the impact of the incumbent variables on the performance. In this study, application the metamodelling technique reveals the correlations among the design variables and the magnitude of effect of each variable on the product, i.e. the PHEV performance on the road. This method helps assessing our desired family design problem to evaluate the potential of the chosen variants for family design and platform configuration. The only powertrain family design study that exists so far in the literature is by Fellini, Papalambros, and Weber (2000), where a family of three powertrains, including a conventional vehicle, an EV and a mid-sized parallel configuration HEV powertrain is assessed. Techniques such as derivative-free global optimisation and decomposition techniques are explored for addressing the challenges resulting from the high level of the design complexity in their study. As such, this study is the first of its kind in assessing platform configuration and family design for PHEVs.

3. The proposed method

The proposed PFD methodology in this study includes identification of proper candidates for the family (explained in Section 3.1). The candidates are called variants which are selected based on market segments identified through the literature review of PHEV market. The next stage is optimizing each variant, and then the platform configuration is identified through the strategies that will be explained in Section 3.2. The best value of each platform variable is determined afterwards (as per Section 3.3), through a strategy called partitioning strategy. Once the configuration is identified and values of all platforms and sub-platforms are determined (in Section 3.4), the entire family will be optimized and the resulting solution will be compared with the initial individual optima for each variant in Section 3.5. Figure 1 shows these steps in a flowchart format, and the details of each step can be found in Pirmoradi, Hajikolaei, and Wang (2015). A brief explanation of some of the steps is presented below.

3.1. Platform candidates identification

The market segments selection step of this study is done through literature review of the existing market-related studies for PHEVs.

After optimisation of the design for each variant, the vector of optimal values known as x^*, the sensitivity and correlations information is obtained through applying the metamodelling technique, and this enables identification of the platform candidate set. The best candidates for sharing are the variables whose commonalisation results in the least performance loss for the entire family. In other words, for reducing manufacturing costs, it is desired to identify the design variables which can take a common value among more of the family without significantly impacting performance optimality. As such, the proper candidate for a platform or sub-platform is a variable with the least impact on the objective function. Such information on the impact of the variables can be obtained through conventional sensitivity analysis, but for a simulation model like the one in this study, conventional sensitivity analysis is often quite an expensive task due to the large number of samples needed. Step 3.2 will demonstrate this part of our developed methodology.

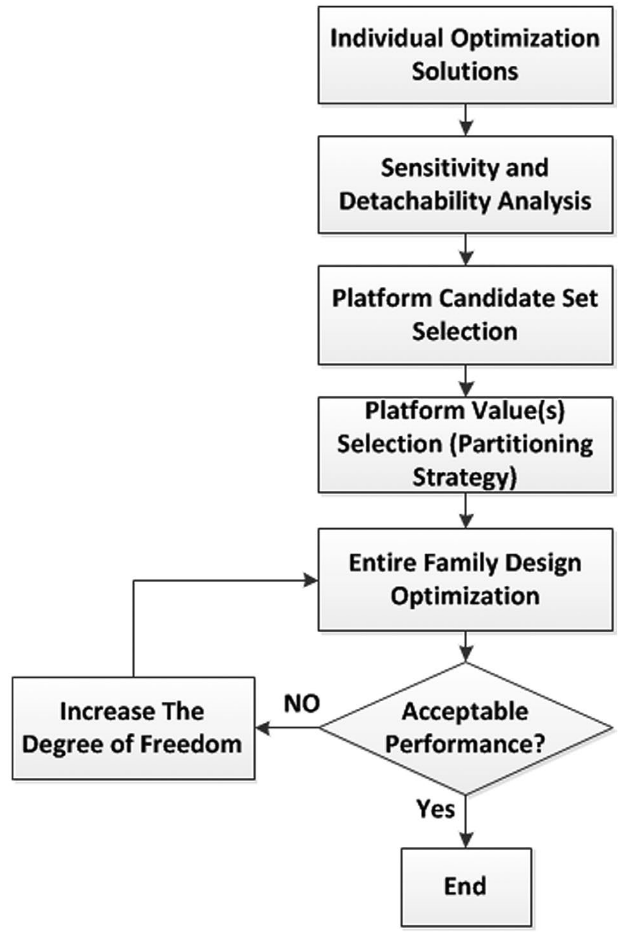

Figure 1. Flowchart of the proposed family design method.

3.2. Sensitivity and detachability analysis

Metamodels are built based on sampling a number of points (or input–output pairs) which allow finding information about the structure of the function under study. Since the required number of samples grows exponentially by increasing the number of variables, extensive sampling can impose remarkable computational costs to the system. The technique used in this study is of advantages to address such issues through combining the radial basis function–high-dimensional model representation (RBF-HDMR) and the random sample HDMR (RS-HDMR).

Metamodelling provides reliable information on the dependencies of complex systems output to several variables/factors based on sampling points (or input-output pairs). HDMR is generally shown in Equation (1):

$$f(x) = f_0 + \sum_{i=1}^{d} f_i(x_i) + \sum_{1\le i<j\le d} f_{ij}(x_i, x_j) + \sum_{1\le i<j<k\le d} f_{ijk}(x_i, x_j, x_k) + \cdots + \sum_{1\le i_1<\cdots<i_l\le d} f_{i_1 i_2 \cdots i_l}(x_{i_1}, x_{i_2}, \ldots, x_{i_l}) + \cdots + f_{12\cdots d}(x_1, x_2, \cdots, x_d) \tag{1}$$

where d is the number of input variables; f_0 represents the zeroth-order effect on $f(x)$, which is a constant; $f_i(x_i)$ is the effect of the variable x_i acting independently on the output $f(x)$ (known as the first-order effect which can be linear or non-linear). The second-order effect $f_{ij}(x_i, x_j)$ is the residual correlated contribution of variables x_i and x_j on $f(x)$ after excluding their first-order contributions through the first-order components, and so on. The RBF-HDMR uses the RBF function to model the component functions Shan and Wang (2010), and it is shown that the variable correlation and the relative strengths of the correlations are estimated well in general by this technique according to Hajikolaei et al. (2015).

After modelling the black-box function through the RBF-HDMR technique, a random sampling-based metamodelling technique (RS-HDMR) introduced by Sobol (1993), and Alış and Rabitz (2001) is applied to calculate the sensitivity indices. The variable correlations quantified through the use of this technique can reveal the variables that have weak mutual effects with the rest of variables (on the product performance). A two-dimensional matrix called the sensitivity matrix S is obtained in this stage. The diagonal elements of the sensitivity matrix show the variables' direct impact on performance (i.e. the first-order impact), and the off-diagonal elements show the variable correlations in a second-order approximation (Li, Wang, and Rabitz 2002; Li et al. 2006). If a variable has low sensitivity, it can be a good candidate for platform configuration.

Through use of the RBF-HDMR and RS-HDMR, the required steps and decisions for platform candidate selection briefly include sorting the variables in non-descending order in terms of their overall effect on the family (into a vector called average sensitivity index (ASI)), and in terms of their correlation with other variables (the resulting vector is called average quantified correlations (AQCs) vector). These two sorted vectors along with a third vector called coefficient of variation (CV) will form the foundation to make decision on which variable(s) to fix or communalise over the entire family, which variable(s) to be partially commonlised (take the same value over a few of the family members), and which variables to keep as non-platform or scale, i.e. taking unique value per family member.

(1) Sensitivity indices ranking: for each variant of the family, through running the metamodelling approach above, a matrix S is obtained, which we call *sensitivity matrix*. This is n by n matrix where the diagonal elements represent the magnitude of each variable on the objective function, and the non-diagonal elements represent correlations between each pair of the design variables. The diagonal elements form a vector that we call sensitivity index (*SI*). In matrix S, once excluding the diagonal elements, each row's maximum value is collected into another vector, which we call quantified correlation (*QC*), the represents the biggest correlation of each variable with the rest of variables, and thus provides information on which variable is most highly correlated to some others among the variables in each variant. Since the *SI* and *QC* vectors are obtained once for each variant, there will be as many of such vectors as the number of variants in the family to design. As such, to obtain a global or aggregated vector, an average of all variants would be required. The resulting average of all *SI* vectors is called the global or *ASI* and, similarly, an *AQC* vector will be obtained once the metamodelling is applied to one variant simulation at a time. By collecting *SI* and *QC* for all the variants, we will have two vectors, *ASI* and *AQC* for each variant. Based on the heuristically determined *SI* threshold, the ***ASImin***, the variables for which the average *ASI* value is lower than ***ASImin*** are selected and recorded as a platform candidate set. This set is called Set #1.

(2) Detachability ranking: through sorting the global or *AQC* measures in a non-descending order, the variables with sufficiently low correlation to the rest of variables are identified and recorded as the second platform candidate set (Set #2). The role of *AQC* vector is to help identifying the biggest threatening variables for communalization. In identification of platform ideas, based on values from the *AQC*, if one of the cases below apply, caution will be required in selecting the candidates for sharing or commonalisation as follows:

   (a) The variables are on the right end of both *ASI* and *AQC* are of least benefit for communalization and better to be kept as scale variable due to their high impact on the objective function, as well as their large correlation and coupled effect along with some other variable.

   (b) If a variable x on the left end of *ASI* shows up to be on the right end of *AQC*, from the S matrices that were used to form the *AQC* vectors (five vectors for five family members), it is required to identify which variable(s) it is mostly correlated to, and the logic is to avoid communalizing both of these variables into single platform, as it may result in more performance loss.

The ultimate set will be sorted in a non-descending order of the *ASI* values, and will be assessed for commonalisation based on the partitioning strategy to be described shortly. Since in this approach the sensitivity analysis is performed on the metamodel instead of the original expensive function, the cost of the sensitivity analysis is remarkably reduced due to the use of computationally inexpensive sample points from the metamodel. Complete details of this approach can be found in Pirmoradi, Hajikolaei, and Wang's study (2015).

3.3. Platform value(s) determination

The basic idea to determine the common value for each candidate variable is to leverage the *CV* parameter information. The *CV* for a single variable aims to describe the dispersion of the variable in a way that does not depend on the variable's measurement unit. This idea is taken from the robust design principles which have been addressed and applied to the PFD by Simpson et al. (1996). Although we have used this idea with some modification and simplifications, the main logic behind both are the same, i.e. to attempt to keep the mean of the new design as close as possible to the target mean, and to minimise the deviation in separate goals. Let the matrix P represent the optimal values for the design variables ($j = 1 \ldots, m$) over the entire family of p products, obtained from the first step when no platform has been used.

x_i^{*j}: The optimal value of ith product for the jth variable

$$P = \begin{bmatrix} x_1^{*1} & \cdots & x_1^{*m} \\ \vdots & \ddots & \vdots \\ x_p^{*1} & \cdots & x_p^{*m} \end{bmatrix} \tag{2}$$

This parameter is shown in Equation (4):

$$\mathrm{CV} = \frac{\sigma}{\mu} \times 100\% \tag{3}$$

$$\mathrm{CV} = \left[\ \frac{\sigma(:,1)}{\mu(:,1)} \times 100\% \quad \cdots \quad \frac{\sigma(:,m)}{\mu(:,m)} \times 100\%\ \right] \tag{4}$$

where σ and μ are the standard deviation and mean operators, respectively. A larger value of this parameter indicates more dispersion of the vector values. Using this parameter as a reference for the platform member selection, the commonalisation scheme is expected to result in the least possible deviation of the variants from their individual optimal value.

This strategy allows single platform configuration for the variables with sufficiently low *CV* values, and attempts to identify the minimum number of multiple platforms with a desired average *CV* after clustering. We refer to this strategy as the optimal partitioning strategy, which includes a clustering step, and then assigning the desired value to each platform or sub-platform. The details of the clustering and platform value determinations can be found in Pirmoradi, Hajikolaei, and Wang (2015).

3.4. Entire family design optimisation

After obtaining the optimal configuration and the values assigned to the platform variables, the design problems with a fewer number of variables will be obtained for each variant, which will be optimized similar to Step 1, with the following problem definition:

$$\begin{gathered} \forall i = 1, 2, \ldots, p \text{ and given the fixed platform from Step 3} \\ \text{Find } x^i_{\text{non-platform(NP)}} = x^i_{\text{NP}_1}, x^i_{\text{NP}_2}, \ldots, x^i_{\text{NP}_{m-N}} \\ \text{To minimize AOF}(x^i, v^i) \\ \text{S.T.} \\ g_j(x^i, v^i) < 0, j = 1, 2, \ldots, n \\ x^i_L \le x^i \le x^i_U \end{gathered} \tag{5}$$

where x^i_{NP} is the non-platform variable for the ith variant and N is the number of platform variables that are now fixed.

3.5. Performance evaluation

The obtained objective function value of each variant will be compared to the individual optimal target values and if the performance change is within the allowed range (i.e. maximum of 10% loss according to the previous studies for the same design problem), the design can be accepted for the family.

In case of violating the performance requirements (obtaining infeasible design), the following strategies will be implemented until a feasible design is obtained:

(1) Considering multiple sub-platforms instead of a single platform, adjust the value of individual variable in order to reduce the variation from the individual optima among the new sub-platform members.
(2) Increase the degree of freedom by adding to the number of non-platform variables, i.e. excluding the last member in the platform candidate set, and optimizing the variant with the new set of non-platform variables.

This methodology is applied to the universal electric motors family design problem and its performance has shown to be better than a number of the existing methodologies such as the one developed by Dai and Scott (2007), Ninan and Siddique (2014), as well as VBPDM (Nayak, Chen, and Simpson 2002), and PPCEM (Simpson, Maier, and Mistree 2001) in terms of being capable of combining two important phases in family design of black-box problems, i.e. metamodelling, and finding the candidates for platform configuration (Pirmoradi, Hajikolaei, and Wang 2015).

In the next section, details of a generic simulation model developed for the PHEVs under study will be first presented, and then step by step application of the proposed PFD approach will be described.

4. Application to the PHEV family design

4.1. Modelling the PHEV

In this study, we built a forward-looking simulation model in Sim Driveline™ (Mathworks 2013) and used the parameters and specifications of components such as the battery from PSAT™ component files library (PSAT). The PHEV model resembles to the MY 2004 Prius with power-split configuration, and the model was validated by comparing performance results to test data available for MY04 and from PSAT (Rousseau, Pagerit, and Monnet 2001). For the fixed parameters and the references for scaling the unfixed parameters, initialization files from PSAT were used and then the built model was first validated through comparing the following output parameters to those available from literature and test labs data: engine torque, power and efficiency profile for an Urban Dynamometer Driving Schedule which is a widely known driving cycle or speed–time profile for the simulations; motor torque and efficiency; battery SOC, temperature, voltage and current over time; and vehicle speed versus drive cycle speed, overall or aggregate torque demand of the vehicle and the actual

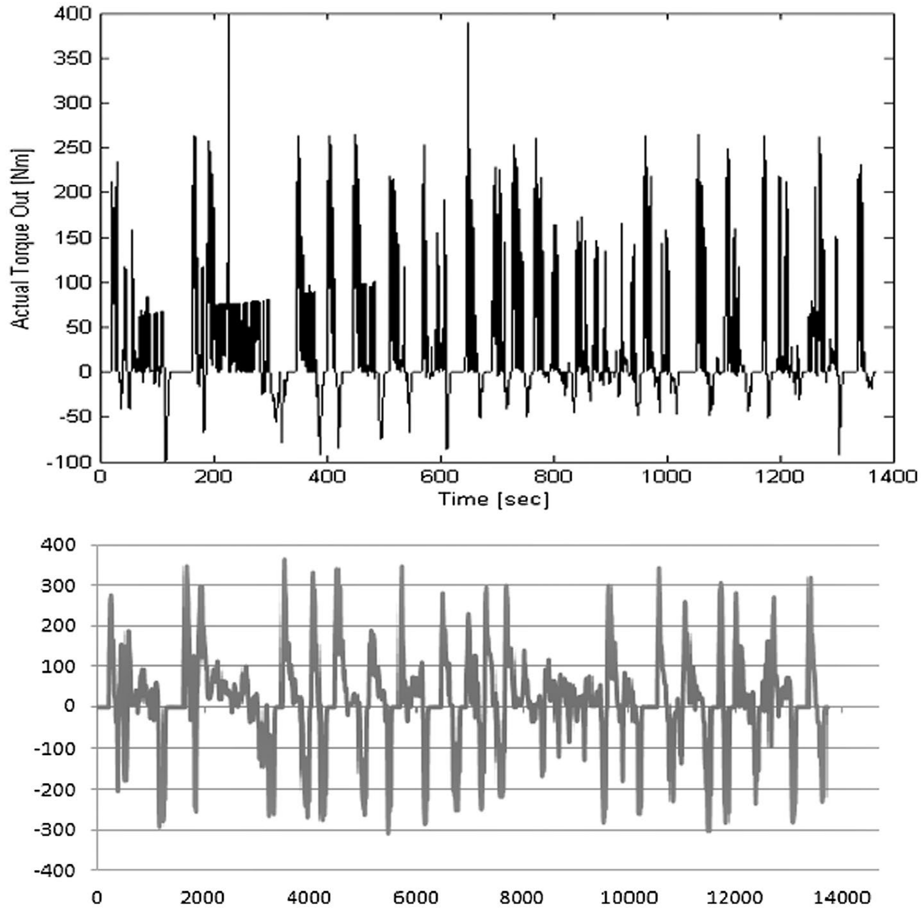

Figure 2. Torque on wheel comparison between test data and simulation model.

torque on wheels over time. All the results showed reliability of the model for further use in design optimisation. Figures 2 and 3 show the validation results for two of the parameters, i.e. the torque on the wheels and the engine torque.

Toyota Prius features a planetary gear set to split the power from the engine. With such power-split configuration, the engine can propel the vehicle alone, or charge the battery through a generator. A traction motor provides another source of power to either assist the engine or independently drive the vehicle. The flexibility of power management makes the power-split configuration more advantageous upon improving the overall efficiency of the vehicle. As such, the planetary gear set is a fundamental component of power split powertrain configuration, consisting of a sun gear, a ring gear, a carrier and pinion gears. The motor is connected to the ring gear and final driveline, the generator to the sun gear and the engine to the carrier. The PSD ratio is defined as the ratio of the number of ring gear teeth to that of the sun gear.

The design variables in our study include a set of component sizes, along with two variables from the control strategy. The control strategy is a blended strategy that enables engine to assist in the propulsion. In this strategy, the vehicle normally operates in the CD mode, but if the torque demand exceeds a specific value, even though the SOC might have not reached the lower limit, the engine is leveraged to assist in propulsion and is then turned off as soon as the required torque is reached, resulting a mix of CD and CS modes. We assess a range of possible values for the power-split ratio, which span from 2.6 to 3.4, according to a study in this area by Li and Kar (2011) that leveraged dynamic programming to find a range of optimal ratios that can split the torque in the component sizes such that the fuel consumption is minimised and the vehicle performance stays within a desired range. For the sake of maintaining discrete nature of the power-split ratio, we defined a new variable as the ratio of the ring gear to the sun gear, and the sensitivity analysis has been performed on a set of seven variables to allow us analyse the impact of each gear ratio separately. The set of variables and their design bounds are:

(1) Upper limit for SOC ($0.6 \le x_1 \le 0.95$).
(2) Lower limit for SOC ($0.25 \le x_2 \le 0.5$).
(3) Engine size ($40 \le x_3 \le 85$) KW.
(4) Motor size ($30 \le x_4 \le 75$) KW.
(5) Number of battery modules ($20 \le x_5 \le 143$).
(6) PSD ratio: $\frac{x_6}{x_7} \in \{2.6, 2.75, 2.9, 3.0, 3.2, 3.25, 3.4\}$

The objectives of interest include fuel economy, emissions and powertrain cost, which are integrated into an aggregated objective function (AOF), based on the principles adopted from Dai and Scott (2006). The AOF is created from integrating the preference functions for each design objective, where each preference function attempts to find a value close to the best value, and not more (or not less) than the worst value. For example, for PHEV$_7$, the preference for fuel economy indicates that any fuel economy more than 90 miles/gallon can be considered satisfactory, with a high preference, while any fuel economy below 70 miles/gallon

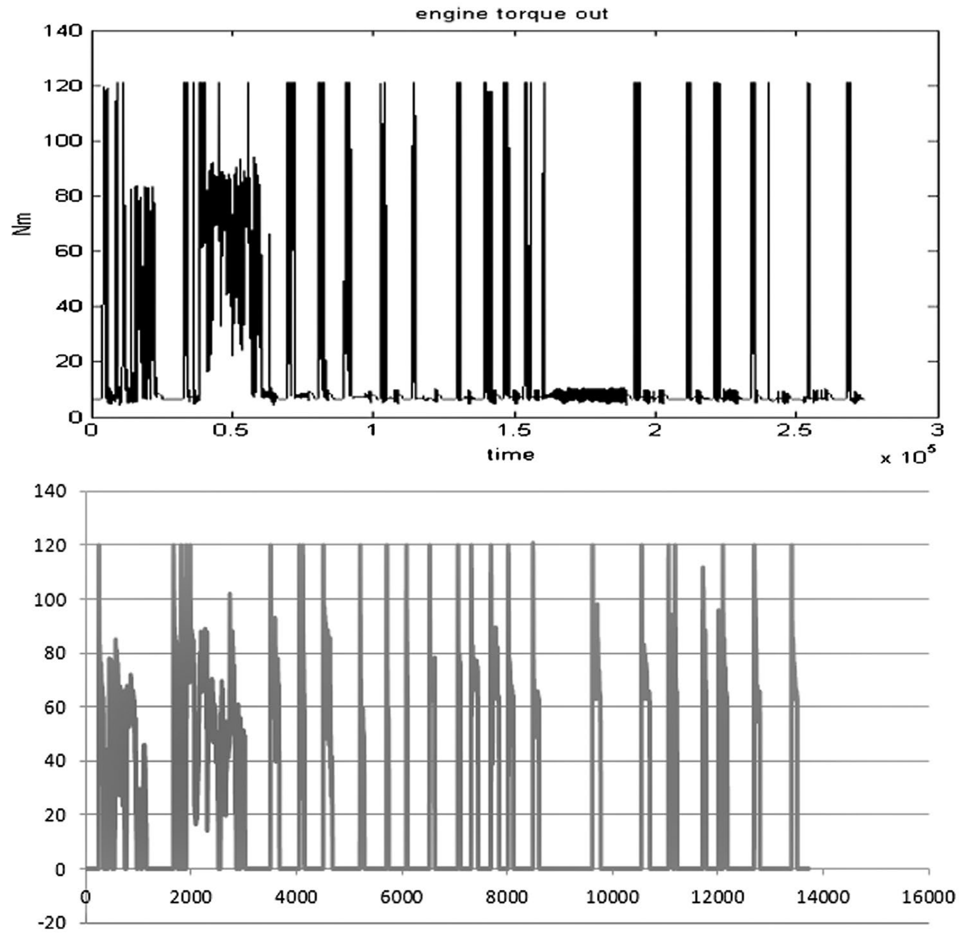

Figure 3. Engine torque comparison between test data and simulation model.

is considered unacceptable, or with a low preference. As such, the weighted aggregation of these three functions allows a single-objective optimisation.

The AOF of this problem is as follows:

$$\mathcal{P}_s = \left(\frac{\omega_1 \alpha_1^s + \omega_2 \alpha_2^s + \omega_3 \alpha_3^s}{\omega_1 + \omega_2 + \omega_3} \right)^{1/s} \tag{6}$$

$$\text{Fuel Efficiency} \quad \alpha_1 = \frac{f_1 - f_{1\_\text{worst}}}{f_{1\_\text{Best}} - f_{1\_\text{Worst}}} \tag{7}$$

$$\text{Cost} \quad \alpha_2 = \frac{f_{2\_\text{Worst}} - f_2}{f_{2\_\text{Worst}} - f_{2\_\text{Best}}} \tag{8}$$

$$\text{CO}_2 \text{ Emissions} \quad \alpha_3 = \frac{f_{3\_\text{Worst}} - f_3}{f_{3\_\text{Worst}} - f_{3\_\text{Best}}} \tag{9}$$

$\mathcal{P}_s$: aggregated preference function.

α_i: preference function for ith objective of interest.

f_i: objective function value for ith objective.

Table 1. The vehicle dynamics specifications for simulation.

Parameter	Feature/value
Drag coefficient	0.26
Frontal area	2.25 m^2
Glider mass	1228 kg
Engine	1.5-L, 40–85 kW, Atkinson 4 cylinder; 5000 rpm maximum speed
Motor	30–75 kW, 400 Nm, 6500 rpm maximum speed
Generator	30 kW, 10,000 rpm maximum speed
Battery	Li-ion Saft, Series, 3 cells per module, 20–143 NBM
Final drive ratio	4.113
Wheel radius	0.305 m

f_{i_Worst} & f_{i_Best}: the function value below (or above) which, is not desired.

ω_i: weight of the ith objective.

s: level of compensation among objectives in hand.

As noted by Dai and Scott (2007), adjustment of the set of these decision parameters (i.e. $p = \omega_i, s, \alpha_i$) will result in the best platform decision. However, the efficacy of the method does not depend on an optimized set of such parameters. Since the focus here is on finding information on the relation and impacts of the design variables rather than performing optimisation, the weights are chosen to be equal, i.e. $1/3$, and s is -1.

The general specifications of the simulated vehicle are shown in Table 1. It is assumed that all of the vehicles have the same distance between charges, which is beyond the highest AER (60 miles), and therefore no charging happens during the drive cycle.

In order to decide which variations of PHEVs would be the most appealing to different customer segments, a thorough review of the research in the following areas were conducted in this study: (a) the studies which have performed market penetration scenario analyses; (b) the ones that have conducted surveys in order to analyse customer behaviour/preferences and find more about their perceived benefits in regard to these vehicles; and (c) those which have assessed customer data from resources such as National Household Transportation Survey to identify the best fit among available vehicle designs, for various segments. The details of these studies can be found in Simpson (2006), Rousseau et al. (2007), Kurani, Heffner, and Turrentine (2008), Santini and Vyas (2008), Shiau et al. (2009), Abe (2010), Axsen and Kurani (2010), Lin and Greene (2010), Skerlos and Winebrake (2010), and Egbue and Long (2012). An important observation from the review of the market studies is that PHEV design optimisation problems are of a multi-objective nature, implying that not only many parameters affect the performance, but also the performance can be defined and assessed from various aspects. For example, Shiau and Michalek (2009) found that the optimality of the x miles and the chosen vehicle (between HEV and PHEVs) highly depends on what objective is under consideration. As such, the vehicle with minimised GHG emissions might be different from the one designed for minimised life time cost or the fuel consumption.

In this study, based on a review of the existing research in market side of the PHEVs and studies related to consumers' behaviour/preferences, five variants are selected for our family design with a nominal AER of 7, 20, 30, 40 and 60 miles in this study. The chosen powertrain configuration is the power-split PHEV which takes advantage of both parallel and series configurations. The scale-based family design is of interest for PHEVs in this study, assuming that all the variants will have the same configuration.

4.2. Steps of the family design method

Step 1: Individual optimisation

In a typical PFD approach the design variables along with their optimal values for each variant have to be identified first. According to the literature, this can be obtained through optimisation of the design for specific performance expectations, or can be adopted from the literature. The preference function needs the values shown in Table 2 to find a value close to the best value, and not more (or not less) than the worst value.

The constraints are shown in Table 3.

Each variant is optimized toward its specific objective function. The algorithm used for optimizing the variants is TRMPS2 algorithm which is an adaptive metamodel-based optimisation methodology and can be found in detail in Cheng et al.'s study (2015). The results of optimisation are shown in Table 4.

Table 2. Selected range for different objectives.

Variant	1	2	3	4	5
			Fuel economy (miles/gallon)		
Best	90	85	80	75	65
Worst	75	65	60	55	42
			*Cost (*1000) $*		
Best	2.5	3	3.3	3.6	4
Worst	3	3.5	4	4.5	5
			Emission (grams/mile)		
Best	130	150	165	180	205
Worst	145	170	185	200	230

Table 3. The system constraints for the PHEV design problem.

Time from 0 to 60 mile/h (or 95.56 km/h)	$t_1 \leq 12$
Time from 0 to 85 mile/h (or 136.79 km/h)	$t_2 \leq 23.4$
Time from 40 to 60 mile/h (from 64.37 to 95.6 km/h)	$t_3 \leq 5.3$
Maximum acceleration (ms^{-2})	$0.5 \times g \leq$ max acceleration
Travelled distance within the first 5 s	140 feet (or 42.6 m) ≤ 5s_distance
Maximum grade ability percentage at 55 mile/h	6.5% ≤ max % grade
Maximum speed	85 mph ≤ max speed

Table 4. Individual variants design optimisation solutions.

Variant / Design variable	P_1	P_2	P_3	P_4	P_5
x_1	0.79	0.94	0.94	0.90	0.93
x_2	0.25	0.28	0.34	0.34	0.30
x_3	83885	84697	84945	84366	83717
x_4	48346	50125	53623	54033	55467
x_5	20	42	71	75	88
x_6	78	79	82	81	80
x_7	29	27	27	27	25
Fuel efficiency (miles/gallon)	198.4	192.73	187.15	113.9	97.03
Cost ($)	2820.8	2860.6	2936.9	2944.9	2975.1
CO_2 emissions (grams/mile)	154.47	155.94	157.78	170.7	180.83
AOF	2.25	1.27	1.93	1.87	1.74

Step2: Platform candidate selection

The graphical presentation of the simulation output versus the metamodel output shows high conformance or accuracy. However, to have a quantified measure of the accuracy, the widely known accuracy measures such as R-square is 0.9981, and root mean square error value is 0.1385.

R-square shows the accuracy in sampling points (Shan and Wang 2010). The metamodel accuracy was assessed for the sampled points, and the results of this comparison are shown in Figure 4, where 1000 sample points were generated and the output of the simulation model is compared to that of the metamodel on each of the sample points. Since all the 1000 samples output would not be easy to show, for the sake of increased readability, a snapshot of the entire plot is provided here, where the Matlab plot is zoomed in on the area between 400th and 550th sample points. Other accuracy measures include relative average absolute error (RAAE) and root mean absolute error which are measures of prediction accuracy of the metamodel and are desired to be small. RAAE in our study is 0.02, and the RMAE is 0.49 which indicates reduced accuracy in some local areas of the design space.

The number of expensive sample points per variant metamodelling is shown in Equation (10):

$$\text{Number of expensive samples} = 1 + 2 \times \text{Number of variables} + \binom{\text{Number of variables}}{2} \tag{10}$$

This value is equal to 36 for each design problem, and in total is 180 for the entire family metamodelling.

As explained earlier, first SI vectors for five variants are obtained through applying the RBF-HDMR and RS-HDMR to

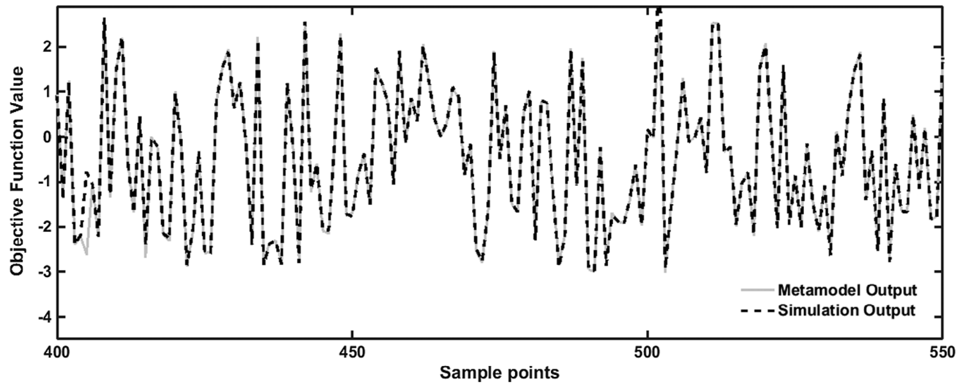

Figure 4. Metamodel accuracy for 150 sample points.

Table 5. Local and global sensitivities of variables in the PHEV family design problem.

Design variable	x_1	x_2	x_3	x_4	x_5	x_6	x_7
SI(1)	0.0008	0.0003	0.0025	0.9242	0.0006	0.0030	0.0003
SI(2)	0.0086	0.0139	0.0150	0.5933	0.0105	0.0039	0.0110
SI(3)	0.0098	0.0083	0.0321	0.2588	0.0095	0.0196	0.0030
SI(4)	0.0110	0.0114	0.0468	0.1048	0.0126	0.0014	0.0015
SI(5)	0.0151	0.0395	0.0444	0.0282	0.0372	0.0132	0.0265
Global (average) *SI*	0.0091	0.0147	0.0282	0.3819	0.0141	0.0082	0.0085

Table 6. Quantified correlation of variables in the PHEV family design problem.

Design variable	x_1	x_2	x_3	x_4	x_5	x_6	x_7
QC (1)	0.0060	0.0055	0.0067	0.0066	0.0067	0.0066	0.0034
QC (2)	0.0344	0.0185	0.0185	0.0344	0.0385	0.0385	0.0271
QC (3)	0.0353	0.0508	0.0742	0.0384	0.0508	0.0742	0.0381
QC (4)	0.0665	0.0644	0.0665	0.0460	0.0625	0.0551	0.0644
QC (5)	0.0546	0.0463	0.0463	0.0546	0.0901	0.0901	0.0588
Global (average) *QC*	0.0394	0.0371	0.0424	0.0360	0.0497	0.0529	0.0384

the design problem. After obtaining the *SI* values for each variable in each variant, a global *SI* is calculated for each variable, which is the average of the five local *SI* values. The obtained *SI*'s and *ASI* are presented in Table 5. Similarly, the *QC*s among the variables for each of the five variants, i.e. PHEV7, PHEV20, PHEV30, PHEV40 and PHEV60 are obtained as shown in Table 6.

Non-descending sorted index of *ASI* and *AQC*:

$$\text{ASI} = [\ 6 \quad 7 \quad 1 \quad 5 \quad 2 \quad 3 \quad 4\ ]$$

$$\text{AQC} = [\ 4 \quad 2 \quad 7 \quad 1 \quad 3 \quad 5 \quad 6\ ]$$

4.2.1. Analysis and findings on platform configuration potential

The sorted *SI* vector shows that the numbers of teeth for the ring gear and the sun gear (in the PSD), x_6 and x_7, respectively, are the least impacting factors on the performance of the vehicle. This might be due to the narrow range for these teeth numbers that assure meeting the performance requirements. Also, since these gears are connected to the component sizes, it is expected that their impact is mostly depending on the chosen sizes for the underlying component. As such, their own impact is not as much concerning as that of the component sizes in changing the output of the objective function. Accordingly, from the commonalisation perspective, a fixed PSD gear ratio can be a promising candidate towards the family design of PHEVs.

The next rank set of impacts relates to the upper and lower bounds of SOC and the battery modules (x_1, x_5, x_2). For the upper and lower SOC, since they are control strategy parameters, they are not expected to be as much impactful as the component sizes. However, the proximity of effect of NBM to the effect of x_1, and x_2 makes sense since the battery size and its SOC window are a set of highly coupled parameters governing the electric power supply for the vehicle. It should be noted that for x_1 and x_2, there is no benefit or manufacturing cost saving in choosing any shared value.

The engine size, x_3, comes next in the *SI* sorted vector. Though in the *SI* ranks, it seems that the engine is on the extreme right side of the sorted *ASI* vector, but all the *ASI* values except for the motor size are quite similar and in a range less than 0.03, which is significantly less than the *ASI* value for x_4, i.e. 0.38 or more than 10 times. As such the engine size can be considered for commonalisation to some extent as well. While further determination of its potential for being a multiple sub-platforms versus the need for keeping it as a scale variable can only be possible after the detailed family design is obtained, however, the insight provided from the sensitivity analysis can be beneficial for manufacturers and designers in the early stages.

At the extreme right side of the sorted *SI* vector, the motor size, x_4, with a high *SI* value, which indicates significant impact of the motor size on the PHEV performance, and potentially, significant performance loss for commonalisation of this variable. Since the engine is able to be decoupled from the propulsion sources and because it can be controlled to operate in its most efficient mode, it is expectable that its impact on the performance can be less than the impact of the electric motor. The highest impact of the motor size comes from the fact that appropriate battery size would not result in the desired performance of the vehicle, unless the motor is also of the right size to be powered by the battery and transfer the power to the transmission. The whole observations discussed above are consistent with the logic of automatic component sizing, which is one of the widely used component sizing strategies. In that strategy, the motor size that meets the peak mechanical power required to follow the desired

Table 7. Suggestions for commonalisation based on the sensitivity and correlation analysis findings.

Variable	Platform configuration suggestions
1, 2	No benefit in commonalisation
3, 6, 7	Candidate for single or multiple platforms
4, 5	Scale variables or potential multiple platforms

driving cycle is the very first item to be determined. The battery peak discharge power is then defined as the electrical power that the motor requires to produce that peak mechanical power. The engine is then sized to achieve the gradeability requirement of the vehicle and the 0–60 mph performance requirement according to Sharer et al. (2006) and Moawad et al. (2009).

In the *AQC* vector, x_6's highest correlation shall be checked back from the individual S matrixes, and by taking average of each pair-wise correlations on the five *S* matrices, x_6 shows the highest correlation with x_4 or the motor size and with x_5 or the battery size afterwards.

The observations on this section are summarised in Table 7. Since another effective parameter on making platform configuration decisions is the *CV*, the decision on whether a variable such as the motor size is beneficial or disadvantageous for any commonalisation level highly depends on the span of the optimal values for any given variable on the variants under study, as well as the expected performance range for the variants. In other words, even the high ranks of SI value will not preclude a variable from being a good option to take a common size, for some variants if not all of them.

Step 3: Platform value(s) determination

As per the structure of our platform configuration strategy, at this step an additional parameter towards decision-making is to find the CV for the vector of optimal values from step 1.

The CV value for each variable is obtained and the resulting vector is:

$$CV = [7.0711\ \ 12.9097\ \ 0.6184\ \ 5.6657\ \ 46.6504\ \ 1.9520\ \ 5.2378]$$

Non-descending sorted index of *CV* vector:

$$[\ 3\quad 6\quad 7\quad 4\quad 1\quad 2\quad 5\ ]$$

The partitioning scheme is determined based on the range of obtained values for *ASI* and the *CV* values, to allow multiple platforms. While the *CV* and *SI* values might recommend keeping specific variables as scale or non-platform variables, however, the assessments of the universal electric motors family problem in Pirmoradi, Hajikolaei, and Wang (2015) reveals that commonalisation of those specific variables (i.e. recommended to be non-platform variable) might also be possible, at least to some extent. A cautious commonalisation of the variables at the right end of the non-descending sorted vectors of *SI* and *CV* not only may not result in significant performance loss, but also may result in savings due to a higher degree of commonalisation. Besides, in case of exceeding the allowed performance loss, it is always possible to increase the degree of freedom and reduce the commonality level. As such, we are willing to implement a moderate scheme where more possibilities of commonalisation were provided to most of the variables. The platform candidates are accordingly obtained as shown in Figure 5, where the left block shows the mapping of variables to platform or sub-platforms based on *SI* and *CV* values, and the right block shows

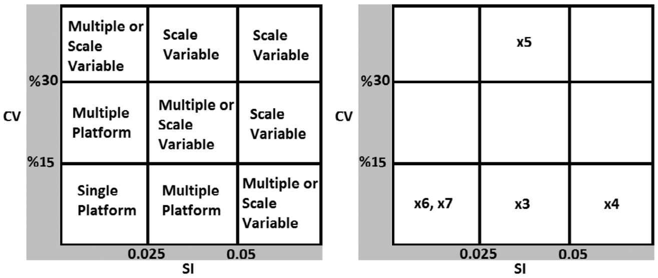

Figure 5. The partitioning scheme for the variables in the PHEV family design problem based on CV and SI.

Table 8. The determined number of platform/sub-platforms for the proposed method.

Variable	Commonalisation level
6, 7	All-or-none platform
3, 4	2 sub-platforms
1, 2, 5	Scale variable

Table 9. Platform configuration of the variants based on the proposed partitioning scheme.

Platform candidate	x_6	x_7	x_3	x_4
Number of platforms	Single platform		2	2
Platform variants			P_1: $\{p_1, p_5\}$ P_2: $\{p_2, p_3, p_4\}$	P_1: $\{p_1, p_2\}$ P_2: $\{p_3, p_4, p_5\}$
Platform preferred value	$x_6 = 81$	$x_7 = 27$	$x_3\ (P_1) = 83801$ $x_3\ (P_2) = 84670$	$x_4\ (P_1) = 49236$ $x_4\ (P_2) = 53865$

the arrangement of design variables for the PHEV family design problem under study, based on application the mapped from the left block.

The next step is to determine sub-platform values for the multiple platform candidates and common value for single platform candidates. By applying the clustering strategy to the multiple platform candidates, the values and sub-platforms suggested through our developed algorithm is shown in Table 8 and the best values for commonalisation is shown in Table 9.

The values of sub-platforms are obtained through applying a *k*-means clustering strategy developed in Pirmoradi, Hajikolaei, and Wang (2015). The two sub-platforms suggested for engine size and motor size result in groups of variants whose *CV* value is reduced by 70%, as compared to the case of a single platform for these variables. For the motor size, since there is a significant variance for the *SI* values, the best suggested value by our algorithm is the weighted average for sub-platform 2, where the *SI* values span the range of [0.02, 0.25]. This makes sense in terms of the algorithm vision that is avoiding performance loss by staying as close to the optimal values from step 1 as possible. Therefore, when variants 3, 4 and 5 are suggested to form a separate sub-platform for this variable, obviously variant number 3 gets a higher priority due to its larger SI value on x_4.

Step 4: Entire family design optimisation

With the determined platform values, we can optimize each variant with less number of variables by choosing the values of platform variables to be the fixed values determined in Step 3. The results of the entire family design are shown in Table 10, along with the obtained efficiency, emissions and cost for each variant. The commonalized values are shown in hatches and shaded cells for an illustrative presentation of the multiple platform family design.

Step 5: Performance loss measurement

At this stage, the best reference for assessing the obtained family design solution is the individual optimal designs from Step 1. By pair-wise comparison of each variant on the new values and individual optima for the three objectives as well as the AOF, the percentage of change in each variant performance is measured and collected in Table 11.

The interpreted values are 10 MPG reduction in fuel efficiency, \$20 cost reduction and 3 g/mile increase in CO_2 emissions in the design of this vehicle after the platform configuration. The acceptability of such amount of loss on a given objective depends on factors such as the ultimate priorities set by the manufacturer to keep the objective values strictly close to specific values. The average performance loss (i.e. 1.52%) is within the nominal acceptable performance loss range. In addition, as noted, the majority of the driven miles per day is less than 30 miles for 50% of the drivers in the US, which makes this specific loss less important, for $PHEV_{60}$. As such, in the case of the PHEV design family, due to the reasons enumerated above, it may or may not be considered an unacceptable performance loss to have 16% reduction in the AOF value. In summary, the obtained family solution is acceptable and no further remedial action might be needed to reduce the commonality level obtained.

Step 6: Comparison with individual optimal designs

The results show that for fuel efficiency objective, the performance loss is 9.8% or about 10 miles per gallon reduction at the maximum for $PHEV_{60,}$ in case of sharing the variables as per the suggested configuration as compared to the expected performance of the $PHEV_{60}$ at its optimal design before family design. There are some improvements for $PHEV_7$ and $PHEV_{40}$, indicating better performance of the vehicle with the new component sizes. The average loss for the entire family on the fuel efficiency is 1.1%, which is within the acceptable loss range.

The losses on the cost objective are all less than or about 1%, indicating insignificant increase in the cost after commonalisation. The biggest increase on the cost is for $PHEV_7$ that is \$20 in a scale of ~ \$2800. Cost reduction has come at the price of reduced fuel efficiency or increased emissions, and the rules of non-domination in multi-objective optimisation are still applicable here.

A quite similar variation in the emission objective values can also be recorded, as all the ups and downs in the emission after the family design stage are less than 1.5%, that is about 3 g per mile of CO_2, as compared to the range of 180 g/mile. As expected, fuel efficiency and emissions are moving in the same direction, i.e. the variants with improved fuel efficiency after the commonalisation have reduction in their emissions, and vice versa. However, there is not such a straightforward relation between the trends for fuel efficiency and the cost.

AOF values before and after family design show more changes, as compared to the individual objectives of interest. $PHEV_7$ and $PHEV_{40}$ have better AOF values after the commonalisation by 5.7 and 3.7%, respectively, and $PHEV_{30}$ and $PHEV_{60}$ have lost 1.3 and 16% of the AOF after the commonalisation, respectively. The 16% loss of performance on the AOF value for the PHEV60 is worth more consideration. Since there is no benchmark to allow assessing this value as an acceptable loss, or a design that would need modification, we may only dig into the loss in individual objectives of interest in order to conclude on this fairly considerable AOF loss.

Table 10. Family design solution by the proposed method.

Variant Design variable	P_1	P_2	P_3	P_4	P_5
x_1	0.8100	0.8578	0.9334	0.9292	0.9497
x_2	0.3388	0.2979	0.2554	0.2786	0.2551
x_3	83801	84670	84670	84670	83801
x_4	49236	49236	53865	53865	53865
x_5	20	52	52	65	70
x_6	81	81	81	81	81
x_7	27	27	27	27	27
Fuel efficiency (miles/gallon)	203.82	189.98	184.55	118.99	87.45
Cost (\$)	2840.0	2841.3	2941.7	2941.7	2940.5
CO_2 emissions (grams/mile)	152.54	156.07	157.83	169.60	183.09
AOF	2.39	1.27	1.91	1.94	1.46

Table 11. Comparison of our method to the individual optima.

Variant	Difference (%)			
1	Fuel efficiency	Cost	Emissions	AOF
2	2.7319	0.6807	−1.2494	5.7778
3	−1.4269	−0.6747	0.0834	0
4	−1.3893	0.1634	0.0317	−1.0363
5	4.4688	−0.1087	−0.6444	3.7433
Average change	−9.8732	−1.1630	1.2498	−16.0920

In addition to comparing the objectives and AOF value for each approach, a comparison on the level of commonality achieved through each solution can help to evaluate the efficiency of suggested schemes. Several indices and metrics have been developed for providing insight into the level of commonalisation obtained for a family design. We have adopted the commonality index (CI) developed by Martin and Ishii (1996) varies between 0 and 1, and provides a measure of the percentage of commonalisation in the whole family. It can be interpreted as the ratio of the number of unique components to the total number of parts (Thevenot and Simpson 2006). For a scalable family, where there is equal number of design components for all the variants, CI is defined as follows:

$$CI = 1 - \frac{u - n}{n(p - 1)} \tag{11}$$

For this design problem, with p variants (i.e. 5) and n components in each variant (or design variables in our case to be 7), for a design with u as the total number of unique components (i.e. 15 as per our obtained family solution in Table 11), the value obtained for this family design solution is 71.4% which is a fairly high value for the family. The normal range for CI is from zero (indicating no sharing), to one (indicating the differentiation in the family is obtained through the minimum number of unique components (i.e. n differentiating components)).

4.3. *Effect of varying the number of sub-platforms (k) on the family design*

In order to investigating the effect of the number of sub-platforms on the performance of the resulting family, we compared three cases, i.e. a single platform for a variable with high SI value,

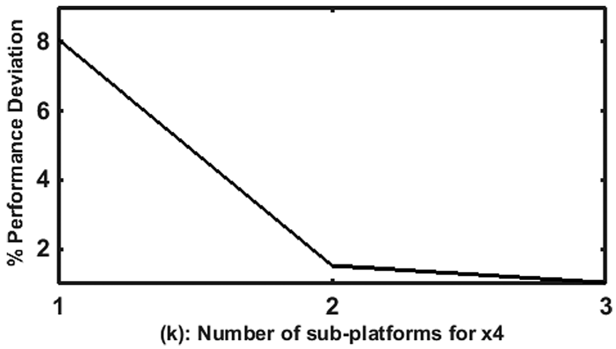

Figure 6. Performance deviation per k for $X4$.

2, and three sub-platforms for the same variable. The motor size is the best candidate to assess such consideration for, based on its high impact on the objective function value. After optimizing the entire family for each case and comparing the family performance with individual's optimal performance, the plot in Figure 6 shows the trends of performance loss per k (i.e. the number of sub-platforms) for the motor size. The benefit of two sub-platforms over all-or-none platform can be concluded through the remarkable reduction seen in the deviation from optimal performance. Similarly, beyond two sub-platforms no significant gain is obtained. This comparison confirms that the suggested platform configuration for the entire family is optimal in terms of the trade-off between commonality savings and performance loss.

5. Concluding remarks

In this study, a sustainable design methodology is proposed to enable scale-based family design for five PHEVs. The selected PHEVs are chosen based on the recommendations of the existing research studies in the literature, as the attractive variants to meet needs of various customer groups in the current market of North America. The proposed family design method involves identification of the promising platform candidates through a metamodelling-based approach that is efficient and cost-effective for expensive simulation-based design problems. Through a non-conventional sensitivity and correlation analysis, the proposed method leverages a combination of well-known techniques such as clustering, CV information and a partitioning strategy towards identification of the best platforms and sub-platforms, as well as the best values for each platform and sub-platform per each variable of the family design problem under study. The method is verified through a test problem from the literature and is shown that the commonalisation strategy and the decision criteria for commonalizing the selected design variables can make an efficient methodology in terms of computational costs and overall performance of the obtained family solution. Since studying the vehicle performance is only possible through expensive simulations, the proposed approach has the capability of handling such expensive black-box design problems without significant computational costs.

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Disclosure statement

No potential conflict of interest was reported by the authors.

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