

Fuel Cell Hybrid Electric Vehicle Sizing using Ordinal Optimization

Sami H. Karaki, Rafika Dinnawi, Rabih Jabr, and Riad Chedid
American Univ. of Beirut

Ferdinand Panik
University of Applied Sciences Esslingen

ABSTRACT

An optimal design methodology is developed in this paper for fuel cell hybrid electric vehicles (FCHEV) based on ordinal optimization (OO) and dynamic programming (DP); the optimal design aims to determine the appropriate sizes of the hydrogen tank, fuel cell, battery, and motor for the purpose of minimizing investment and operational cost given some specification of the car range, the road type and its gradeability. The DP simulates the operation of the vehicle for a set of specified components' sizes for given driving cycles and provides the total vehicle cost per year. The OO method offers an efficient approach for optimization by focusing on ranking and selecting a finite set of "good enough" alternatives through two models: a simple model and an accurate model. The OO program uses the specified sizes of the components that uniformly sample the search space and evaluates these designs using a simple but fast model. As per OO theory, the evaluated designs are sorted in an ascending order and the top- s design solutions are selected. An ordered performance curve method is used to determine the size of the top- s set of "good enough" designs which are then evaluated using an "accurate model" in a kind of horse race. This model is implemented by taking the whole of the driving cycles and an increased number of states in the dynamic programming solution. In these runs the effect of varying the fuel cell, the battery, and hydrogen costs are investigated; car design results are presented with different optimal sizes for different specifications.

CITATION: Karaki, S., Dinnawi, R., Jabr, R., Chedid, R. et al., "Fuel Cell Hybrid Electric Vehicle Sizing using Ordinal Optimization," *SAE Int. J. Passeng. Cars – Electron. Electr. Syst.* 8(1):2015, doi:10.4271/2015-01-0155.

INTRODUCTION

Fuel cells with proton exchange membranes have been identified as a very promising alternative that may simplify the drive train of cars by replacing the internal combustion engines used in the transportation sector [1]. FCHEV technologies may provide a true solution for the traditional pollution problems associated with vehicles in large cities because they use the nontoxic hydrogen gas as fuel and have just water and heat as outputs. FCHEVs have two power sources, proton exchange membrane fuel cells and batteries, or super-capacitors, to supply the power-train demand load. The cost of running a FCHEV may be optimized at two levels: the design level and the operation level. An optimal design aims to determine the optimum sizes of the car components, which are the hydrogen tank, fuel cell, battery, and motor for the purpose of minimizing the investment. Optimal operation, for a given design, aims to achieve minimum hydrogen consumption and battery degradation.

Researchers initially solved the sizing problem basically by optimizing the operation using formal optimization methods and optimized the components sizing through a simple try and rank algorithm. Tate and Boyd [2] accurately approximated the optimal operation problem as a large linear program to compute the globally minimum fuel consumption over a given drive cycle. This is then used in a sizing algorithm to propose different sizes of battery and

engine and to determine for each design the minimum fuel consumption. Once the designs are obtained they are ranked and the one with overall minimum fuel consumption is selected. Bernard et al [3] followed a similar approach for the sizing but minimized fuel consumption of each design using a global optimizing algorithm based on optimal control theory. Jörg and Shröder [4] astutely indicate that the main problem associated with components sizing is the dependency of the power demand on the weight of the vehicle, and therefore on the weight of each component. They used optimal control theory and non-linear programming where the sizes were considered as control parameters of the closed loop of a control structure with an overall objective of minimizing the fuel consumption over a given drive cycle. Kim and Peng [5] approached the problem in a reverse way by using basis functions of a "pseudostochastic" dynamic programming controller to simulate near optimal operation and non-linear programming to determine optimal components sizing.

Recognizing the role of energy storage devices in characterizing hybrid or plug-in hybrid vehicles, many authors focused their attention on the sizing of energy storage devices. This was discussed by Burke [6] who concluded that the battery storage device in a charge-sustaining FCHEV is sized by the peak power during vehicle acceleration. In such designs the battery operates over a battery state-of-charge (SOC) range well within 10% which extends battery

life. Whereas for plug-in FCHEV the fuel economy can be very high because a large proportion of the energy to power the vehicle comes from grid electricity. Markel et al [7] developed a sizing methodology of battery storage devices in FC vehicles based on their role during fuel-cell start up, power assist capability, and regenerative braking.

For the problem of dependency of the power demand on the component sizing itself, researchers tried using systematic algorithms to search for “optimal” sizes of components using evolutionary methods. Yildiz et al [8] used particle swarm optimization to size vehicle components while meeting critical performance as evaluated by a simplified model of a power split plug-in vehicle developed using the Powertrain System Analysis Toolkit (PSAT) from the Argonne National Lab. Jain et al [9] used multi-objective genetic algorithms to size vehicle components to minimize overall fuel consumption using a charge-sustaining control strategy. Ordinal optimization (OO) is a method for complex optimization problems based on two tenets: ‘order’ comparison is more robust against noise than ‘value’, and ‘goal softening’ where the insistence on reaching the ‘best’ is replaced by finding ‘good enough’ solutions with high probability [10]. Jabr and Pal used OO [11] to determine the location and size of distributed generation in a power system by evaluating many alternative solutions using an approximate but fast method based on linear programming and ranking them according to this evaluation. As per OO theory, there is a high probability that the top- s designs include the actually ‘good’ alternatives, which are then evaluated using a detailed optimal power flow model based on nonlinear programming.

This paper presents an ordinal optimization approach for solving the optimal design of FCHEV. The aim is to determine the suitable sizes of the different car components (hydrogen tank, fuel cell, battery, and motor) for the purpose of minimizing the investment and operational cost. The OO approach consists of three main stages. First a high number of alternatives are uniformly sampled from the large search space. Second, the total cost of operating the FCHEV per year, for each alternative is evaluated using a crude, or simple, but computationally fast model. The alternatives are then ranked in ascending cost order and the top- s solutions are identified. The crude model uses a portion of the drive cycle and DP with a relatively large discretization step with simple components models. Third, the top- s alternatives that have a high probability of being in the “good enough” set are then assessed via an accurate model. A “good enough” solution means that the solution has a high probability to be a good solution. OO theory allows computing the size of the selected subset such that it contains one or several designs from among the top good enough samples with a high pre-specified alignment probability. Every design is assessed using an optimizing algorithm to minimize hydrogen consumption and keep battery degradation at check using DP. The DP approach can suitably simulate charge- sustained and charge-depleting operation by proper lower bound specification and enforcement [12] and as such will be used to develop normal designs and plug-in hybrid designs.

PROBLEM FORMULATION

A system's overview of the power train arrangement corresponding to a hybrid architecture is shown in Fig. 1 below. A FCHEV is propelled by an electric machine that receives its electric input from two dc sources through a dc/ac inverter. A dc/dc converter is used to couple the two power sources, i.e. the polymer electrolyte membrane (PEM) fuel-cell and the battery, and a dc/ac inverter is used to power the electric motor. As per current technology, their sizes will be calculated and provided as output from the ordinal optimization algorithm.

The cost is evaluated for two mixed roads, the Urban Dynamometer Driving Schedule (UDDS) and the Highway Federal Emissions Test (HWFET) drive cycles. The fuel cost ratio is taken as a weighted cost of 0.45 of that of UDDS and 0.55 of that of the HWFET cycle, which is approximately in line with what is proposed in [14]. The cost function J in \$/year is minimized over a set of designs $n=1$ to N and is symbolically described as follows:

$$J = \min_{n=1,N} (\alpha I_C(n) + O_C(n)) \quad (1)$$

A nomenclature of the main variables is given in Appendix A at the end of the paper. The investment cost $I_C(n)$ is determined for a given design size vector: $D(n) = [P_{FC}^{max}, E_{BT}^{max}, H_2^{max}, P_M^{max}]$, where the elements are the sizes of the fuel cell, the battery, the hydrogen tank, and the motor. The optimal design is determined over all N designs for a minimum investment and operation cost evaluated on a per-year basis.

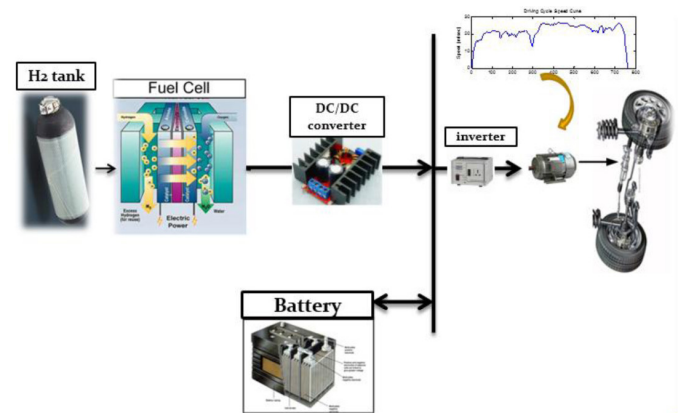


Figure 1. System Overview

So the investment cost is multiplied by the annuity factor α :

$$\alpha = \frac{r(1+r)^l}{(1+r)^l - 1} \quad (2)$$

Optimal Operation using Dynamic Programming

The operating cost in \$/trip is calculated using dynamic programming for one of the two road types and during one trip is given by:

$$O_{C1}(n) = \min \left\{ \sum_{t=1}^T \left[\frac{1}{2} \gamma_{BT} \left(1 + \text{sign}(P_{BT1}(t)) \right) (P_{BT1}(t)) \Delta t \right] \right\} \quad (3)$$

Where $\varphi_{FC}(P_{FC}) = a_n + b_n P_{FC} + c_n P_{FC}^2$ is the cost rate (\$/h) of operating the fuel cell at a level P_{FC} ; the corresponding curve is obtained from the polarization curve of the fuel cell and scaled by the cost of hydrogen fuel. The per-unit curve used in this paper is shown in Fig. 2 and is based on data provided in [14] and [16]. The second term is proportional to the energy delivered by the battery. The proportionality constant γ_{BT} is measured in \$/kWh. Thus the second term is a measure of battery degradation if one considers that a battery over its lifetime delivers a defined amount of energy, approximately. The constraints over one of the road types are:

$$P_{FC1}(t) + P_{BT1}(t) - P_{BR1}(t) = P_{D1}(t) \quad (5)$$

$$0 \leq P_{FC1}(t) \leq P_{FC}^{max} \quad (6)$$

$$P_{BT}^{min} \leq P_{BT1}(t) \leq P_{BT}^{max} \quad (7)$$

$$R_{dFC} \Delta t \leq P_{FC1}(t) - P_{FC1}(t-1) \leq R_{uFC} \Delta t \quad (8)$$

$$R_{dBT} \Delta t \leq P_{BT1}(t) - P_{BT1}(t-1) \leq R_{uBT} \Delta t \quad (9)$$

$$SOC_{min} \leq SOC_1(t) \leq SOC_{max} \quad (10)$$

$$SOC_1(t) = SOC_1(t-1) - \psi_{BT}(P_{BT1}(t)) \Delta t \quad (11)$$

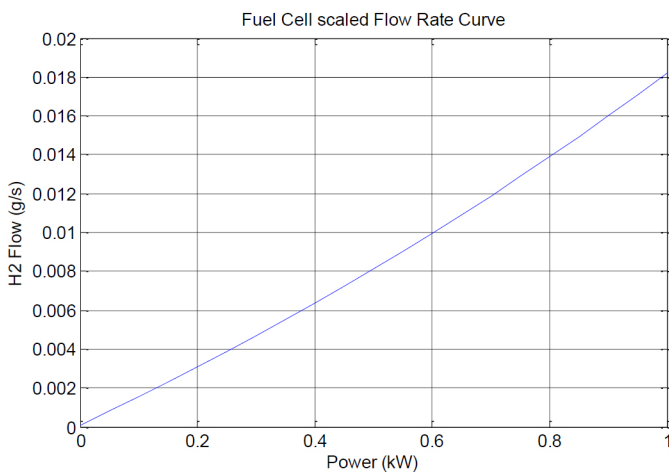


Figure 2. Fuel cell hydrogen consumption curve for 1kW

Equation (5) represents the power balance constraint over every period of the first drive cycle. Constraints (6) and (7) represent the upper and lower limits on the fuel-cell and battery powers, whereas constraints (8) and (9) represent the ramping rate limitations of the fuel-cell and battery. Constraint (10) is the upper and lower limitation on the battery state-of-charge (SOC) and constraint (11) is the dynamic update on the SOC in period t given the battery power and the SOC in period $t-1$.

The $\psi_{BT}(P_{BT1})$ defines a charge power map relating internal energy rate to power output as illustrated in Fig. 3. The above equations are developed for one type of the roads, e.g. the UDDS driving cycle as indicated by subscript 1. Similarly, all the equations from (3), (5), (6), (7), (8), (9), (10), (11) are applied on the (HWFET) driving cycle in order to calculate the total cost per year, $OC_{year}(n)$, for a given design $D(n)$, for the mixed two cycles. The units of OC_1 and OC_2 are \$/trip1 and \$/trip2 respectively, therefore the total cost of M trips per year is:

$$OC_{year}(n) = M(0.45 OC_1(n) + 0.55 OC_2(n)) / 0.7 \quad (12)$$

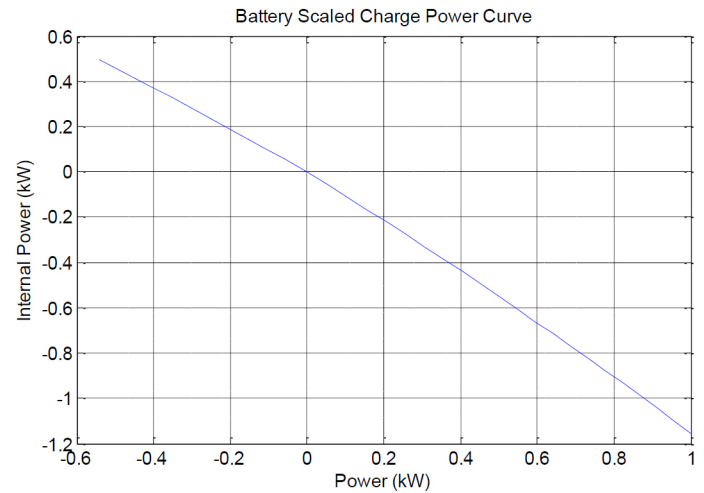


Figure 3. Battery charge map scaled to 1kW

The weighing coefficients 0.45 and 0.55 and the fuel economy adjustment factor of 0.7 to reflect real road driving conditions were adopted from [14]. The number of trips M is 700 based on two trips per day for 350 days per year. In solving the problem using DP, the power demand forecast curve is divided into stages. In each stage the fuel cell power level can be in one of several discrete states, which once fixed, for a given state, it allows the battery power to be determined from the power balance constraint (5). The objective function (3) will be calculated for all the states of stage 1. Then for each state of subsequent stages (i.e. $t=2$ to T), the possible transitions from states of the previous stage $t-1$ are identified, and the minimum cumulative cost of reaching each state is built recursively. When the last stage is reached, the state with minimum cost is recognized, and the preceding states leading to it are identified by a trace-back procedure. Charged sustained (CS) operation may be obtained by setting SOC_{min} to the initial state of charge SOC_0 . Whereas, charge depletion (CD) operation is obtained by reducing SOC_{min} to an appropriate value below SOC_0 . During both modes of operation, the battery cost parameter γ_{BT} is made slightly below (i.e. 10% lower