COMBINING BATTERY AND ULTRACAPACITOR IN PARALLEL TO INCREASE THE OVERALL RANGE OF A PURE ELECTRIC VEHICLE

Final Report

Swetha Viswanatha

1. INTRODUCTION

The eco-friendliness of Electric Vehicles (EVs) compared to gasoline cars has been a topic of discussion and debate for a couple of decades now. A well to wheel analysis conducted by the MIT Electric Vehicle team concluded that EVs indeed consume less energy and produce less Green House Gases (GHG) compared to gasoline cars [1]. While different studies have different conclusions, the debate continues. However, it is important to note that EV's biggest advantage is that it has no tail-pipe emissions. Customers are reluctant to buy EVs for several reasons discussed below.

A fully charged mid-priced EV, for example Nissan Leaf, gives about 70 miles range which is 1/4th the range provided by a fully-fueled gasoline car. In addition, the EV takes up to 8 hours to fully charge. More recently, Fast DC charging stations have been introduced that recharge 80% of the total battery capacity in about half an hour. EVs are more expensive than gasoline cars, for example a Nissan Leaf SV costs about $24,500 after $8,000 tax rebate. The limited range, slow refueling time, and lack of proper charging station infrastructure are the main reasons of "range anxiety" of customers. Previous research done by N. Kang et.al [2] demonstrated an optimal set and distribution of EV charging stations can greatly reduce the "range anxiety" for customers. The paper also describes the EV model developed on AMESim that accepts design variables (of battery, motor, and gear) as inputs and using the simulation outputs, a response surface model was created. The objective was to maximize profit, of the combination of EV sales and services, by meeting the design constraints (range, charging time, speed, acceleration and MPGe).

This project looks at the "range anxiety" from another angle. In order to increase the range of the EV at the system level, this project explores the option of using ultracapacitors as an energy storage unit. In addition to the design variables set by N.Kang et. al., this project includes design variables for the ultracapacitor (i.e., number of capacitors in series and in parallel). However, there will be a trade-off between and EV range and cost, and therefore cost is chosen as a constraint.

The system was modeled on AMESim by making the necessary parameter changes to the sample model, “Electric vehicle – Physical model of electric power train”, provided by AMESim [3]. Additionally, the ultracapacitor block was connected in parallel to the battery in the AMEsim model. A control algorithm was introduced to distribute the power load requirements between the two energy storing units. The design variables are primarily associated with the battery, ultracapacitor, motor, and gear parameters.

2. DESIGN PROBLEM

The following section begins with a problem statement and the assumptions made. It also presents the mathematical and simulation model.

2.1. Problem Statement

The goal of the project is to obtain an optimal set of design parameters (battery and UC size, motor inductance and resistance, and gear ratio) such that the resulting EV range is maximized. This would encourage customers to use EVs not only for short trips but also rely on them for longer trips and thus eliminating the need for two cars. Ultracapacitors have almost unlimited life-cycles, work very well in extreme temperature conditions, are safe and do not overcharge. J.Dixon, et.al, showed an increase in efficiency and acceleration of EVs by combining Li-ion battery and UC [4]; In general, as the EV weight increases (with the addition of UC), the overall vehicle efficiency, i.e., MPGe may decrease and therefore result in a need for a tradeoff. This tradeoff is innately considered in the AMESIM simulation model as the mass of EV is a variable input which is dependent on the battery, UC, motor, and driver mass.

2.2. Assumptions

There are several assumptions made in this paper. It is assumed that the AMESim model will be sufficient to compare design solutions regarding consumption and performances criteria. Also, auxiliary power consumers will be neglected. The voltage across the battery and ultracapacitor connection will be held constant. Only the battery and UC costs are being considered in this project and the other EV costs, including that of motor and gear, are assumed constant.

This project assumes that there are no spatial restrictions for the energy storing units or for other EV components. Also, the UC and battery combination could expel heat that may or may not be accepted. Furthermore, since the UC has low specific energy 5 Wh/kg compared to a battery of

100-200 Wh/kg, the optimal sizing of the UC may or may not meet the EV weight requirements. The upper and lower bounds for the design parameters can be varied depending on the EV manufacturer requirements. Thus, there are several things that need to be taken into consideration, if the optimal solution were to be implemented.

2.3.Mathematical Model

The following sections are used to describe the design variables and their units, mathematical model including the objective and constraints.

Design variables

The following variables and units are used to represent the design objective, parameters and constraints. The design variables were selected based on the model developed and presented in the research paper by N.Kang, et.al. Additional variables and parameters for the ultracapacitors were also considered. Table 1 describes the system, variable name, symbol, and units. The symbols are often used in the rest of the paper and Table 1 can be revisited for clarification.

System	Variable Name	Symbol	Units
Battery	# of cells in series in one branch	n_{Bs}	
	# of cells in parallel in one branch	n_{Bp}	
Ultra Capacitor	# of capacitors in series in one branch	n_{Cs}	
	# of capacitors in parallel in one branch	n_{Cp}	
Motor	Stator inductance	L	mH
	Number of pole pairs	p	
Gear	Gear ratio	N	

Table 1: The table above describes the design variables, associated symbols, and units

Objective function

The objective of this project is to maximize EV range with cost of battery and UC being the inequality non-linear constraint. The range value is calculated based on the simulation outputs- SoC of battery and UC and the distance travelled by the EV using the EPA highway drive cycle.

Design variables **x= [** n_{Bs} , n_{Bp}, n_{Cp}, n_{Cs}, L, p, N **]**

Each of the design variables are constrained by upper and lower bounds as shown below

$\mathbf{x_{min}} \leq \mathbf{x} \leq \mathbf{x_{max}}$

The design variables represented in row vector, **x**, are submitted to the AMESim model as inputs. The battery and UC capacitors weights are calculated and included in the total mass of the EV.

Constraints

The model created on AMESim will provide a range response, *r*, for a given set of design variables combination. There are no other equality constraints considered in this project.

Inequality constraints: To analyze the cost related to the energy storing units, a cost non-linear inequality is considered as shown in eq.1.

Constraint = $(n_{Bs} \times n_{Bp}) \times C_B + (n_{Cs} \times n_{Cp}) \times C_{UC} - C <= 0$ Eq. 1

where C_B , C_{UC} and C are the costs associated with one battery and UC cell and the total budget cost respectively. In this project, C_B , C_{UC} and C are \$10, \$15, and \$8,000 respectively.

Practical constraints: Each of the design variables is constrained by upper and lower bounds as set by feasibility and industry practices and is shown in Table 2 (pg 5).

2.4 Simulation Model

The EV was modeled using a default model available in the AMESIM library: Electric vehicle - Physical model of electric powertrain. The EV model consists of the following components- driver, vehicle, gears, permanent magnet synchronous motor, 3 phase inverter, control unit, motor torque control, battery pack and sensors. The following section discusses modifications made by adding components, a control algorithm, and the parameters values used. The default AMESIM model is shown in the appendix A as Fig. 1 (pg. 14).

Additional components: The goal of this project is to analyze the performance of the electric vehicle using a combination of battery and ultracapacitor (UC) to enhance the overall driving range. The ultracapacitor, a more efficient energy storage system, has low specific energy density but high specific power. While an ultracapacitor is used for peak power demand and supply, i.e., when the car is accelerating and braking, it also reduces the power stress on the battery thus increasing battery life.

AMESIM model was modified by adding an ultracapacitor in parallel to the battery. Volt transducers were added to both battery and UC to read their voltages. A rotatory power sensor was added to the vehicle model to obtain the power load reading. The modified EV model is shown in appendix A as Fig. 2 (pg. 15). A control algorithm was finally implemented to manage the power flow between the motor, battery and UC and is discussed in the following section.

Control Algorithm: A heuristic control algorithm is used to distribute power demanded and supplied between the two storing units. Ideally, steady load power requirements would be satisfied by the battery and any peak, transient power requirements that the battery is unable to supply would be satisfied by the UC. Fig. 3 below shows the interface between electric motor, battery and UC and the input and output currents and voltages.

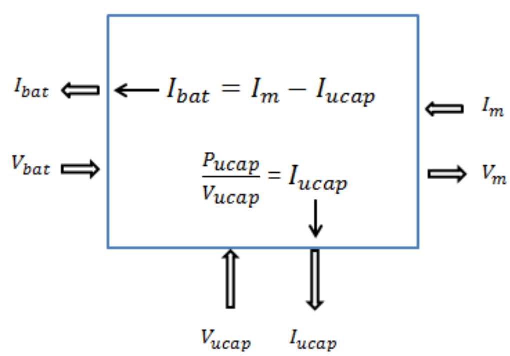

Fig. 3 Interface of the motor, battery and UC and the distribution currents and voltages

where I_m, I_{bat}, I_{ucap} are the motor, battery and UC currents respectively. Similarly, V_m, V_{bat}, V_{ucap} are the motor, battery and UC voltages respectively.

A heuristic power sharing algorithm between a battery and UC was modeled by G.Guidi et al. [5].The control model, as shown in Fig. 4, was adapted with modifications for the purpose of this project. The final output, P_{ucap}, was calculated using this algorithm.

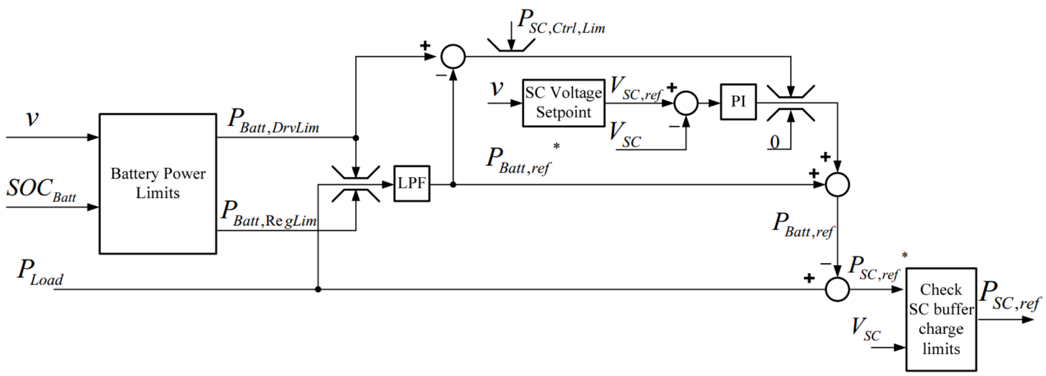

Fig. 4: Heuristic power sharing algorithm between a battery and UC [5]

To obtain the battery power limits, the input to the function **f1**, battery voltage is multiplied by the minimum (- I_{max}) and maximum (I_{max}) current values to obtain battery power regenerative limit, $P_{batt,RegLim}$ and battery power drive limit, $P_{batt,DrvLim}$ respectively . Vehicle velocity, $Vel_{\ vehicle}$ and power load, P_{load} are measured by velocity and power sensors respectively and also serve as inputs to the control algorithm.

The desired UC capacitor voltage, $V_{ucap,ref}$ is a function of vehicle velocity and is represented as **f2** on the AMESIM model and is calculated as shown in Eq. 2.

$$V_{ucap,ref} = \sqrt{{V_{ucap,max}}^2 - \frac{M}{C_{ucap}} * Vel_{\ vehicle}{}^2} \qquad \text{Eq. 2 [5]}$$

where $V_{ucap,max}$ is the maximum voltage of a UC and is a constant. C_{ucap} is the nominal capacitance and depends on the size of the UC as $cap_{UC} = c_{cap} * n_{cB}/n_{cS}$ where c_{cap} is the capacitance of a single capacitor which is considered a constant. M is the total mass of the EV which includes the EV, battery, UC weights, motor and driver. The power supplied by the UC,P_{ucap} is calculated using the following equation.

$$P_{ucap} = P_{load} - P_{bat} \qquad \text{Eq. 3}$$

where P_{load} and P_{bat} are the load and battery power respectively.

With the above modifications, the rest of the control algorithm was modeled as shown in Fig. 4 (pg 6). The modified AMESIM control model is shown in Fig. 5.

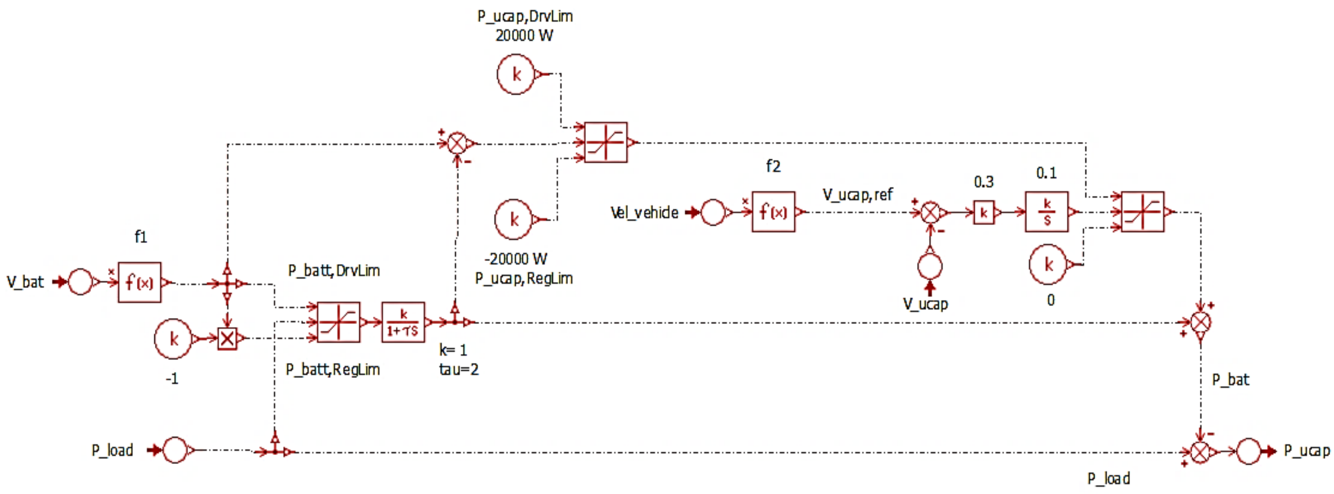

Fig. 5: Heuristic power sharing model modified from [5] and implemented on AMESIM

Parameters considered: The AMESIM model accepts both numerical parameters as well as variables as inputs. To ensure that the MATLAB DOE code can access the EV design parameters, they are defined as global variables. Table 2 describes the design variables set as global. The upper and lower bounds are adapted from Namwoo et al. [2] and modified.

System	Variable Name	Symbol	Upper Bound	Lower Bound
Battery	# of cells in series in one branch	n_{Bs}	50	150
	# of cells in parallel in one branch	n_{Bp}	1	4
Ultra Capacitor	# of capacitors in series in one branch	n_{Cs}	50	100
	# of capacitors in parallel in one branch	n_{Cp}	1	4
Motor	Stator inductance	L	1.5mH	6.0 mH
	Number of pole pairs	p	1	4
Gear	Gear ratio	N	3	15

Table 2: Design variables and their upper and lower bounds

In addition to the design variables described above, Fig 6 describes the full list of the global parameters, units, and initial values used in the simulation model. These initial values were also adapted from the AMESIM model created by Namwoo et al.

Name	Title	Unit	Value
mFvisc	viscous friction on motor shaft	Nm/(rad/s)	0.0003
mFstict	Coulomb (dynamic) friction coefficient	null	1.5
Rs	machine stator resistance	Ohm	0.07
Phif	machine permanent magnet flux linkage	Wb	0.35
Ls	machine stator cyclic inductance	H	0.0034208
Lsd	machine stator cyclic inductance d	H	Ls*0.9
Lsq	machine stator cyclic inductance q	H	Ls*1.1
Imax	Maximum rms current	A	140
p	pole pairs	null	4
N	Gear Ratio	null	9
DC_link	DC link voltage	V	630
V_cell	Voltage of cell	V	0.85
r_cell	Internal resistance of cell	Ohm	0.00127
mMotor	Mass of motor	tonne	0.039493
mHuman	Mass of human	tonne	0.136
Voltage	Open circuit voltage	V	528.2
n_bS	Number of cells in series	null	139
n_bP	Number of cells in parallel	null	1
n_cS	Number of capacitors in series	null	90
n_cP	Number of capacitors in parallel	null	2
Capacity_batt	Nominal capacitance of battery	F	33.1
Capacity_UC	Nominal capacitance of UC	F	33.1
mBattery	Mass of battery	tonne	0.212844
mUC	Mass of UC	tonne	1
mVehicle	Mass of Vehicle	tonne	1.15951

Fig 6: List of global variables, values and their units used in the AMESIM model

The EV model was simulated for the EPA highway drive cycle for 765 seconds and the same was chosen in the *Mission Profile* block of AMESIM. Values for constants such as constant inputs, gain inputs, and time constants are labeled with their corresponding *k* blocks as shown in Fig. 2 (pg. 15).

To realistically evaluate the UC performance, parameters such as voltage and specific power of the K-2 series ultracapacitor of model # BCAP1500 by Maxwell Technologies were used in the AMESIM model [6]. Nominal capacitance of a single capacitor, C_{cap}, used in Eq. 2 (pg. 6) is1500 F.

The simulations assume that the battery is fully charged with SoC (State of Charge) of 100% and the UC starts with SoC of 80%. Staring with a lower SoC value of UC helps to capture energy during regenerative breaking early on in the drive cycle. After the simulation is performed, the model outputs the following response **R=** $[r]$.

3. DESIGN OPTIMIZATION

The following sections describe the steps taken to create the optimization model by performing design of experiments, creating a metamodel and finally obtaining the optimal range value.

3.1 Design of Experiments

Latin Hypercube Sampling was implemented using a simple MATLAB code that sampled 2,000 different values for each of the design variables. This statistical method was used to generate a sample of plausible set of parameter values from a multidimensional distribution. A MATLAB script was created to read all the 2,000 inputs of values between 0 and 1. These numbers were manipulated to fall between the upper and lower bounds of each design variable. The combination of variables **x=** $[\, n_{Bs}, n_{Bp}, n_{Cp}, n_{Cs}, L, p, N \,]$ was passed iteratively into the AMESIM model. The MATLAB code also iteratively read the simulation results, like state of charge of battery and UC, SoC_{bat} and SoC_{UC} respectively, distance travelled, d, etc. All the data was saved on an excel file after each iteration. Range of the EV was calculated using the simulation parameters as shown in the equations below.

$$cap_{bat} = c_{bat} * n_{bP} * 3600 \quad \text{Eq. 4} \qquad cap_{UC} = c_{cap} * \frac{n_{cP}}{n_{cS}} \quad \text{Eq. 5}$$

where cap_{bat} and cap_{UC} are the battery and UC nominal capacitance respectively. c_{bat} and c_{cap}, are the capacitance of single cell and capacitor and are of the values 33.1 Ah and 1500 F respectively.

$$Q_{UC} = V_{avgUC} * \; cap_{UC} \quad \text{Eq. 6} \qquad Q_{bat} = \frac{SoC_{iUC} - SoC_{UC}}{0.95} \quad \text{Eq. 7}$$

where Q_{UC} and Q_{bat} are the charge of battery and UC respectively. SoC_{iUC} is the initial SoC of the UC and is 80%. As mentioned before, for all the iterations, the initial SoC of the battery is

100%. V_{avgUC} is the average voltage of the UC. The distance travelled by an EV is directly proportional to the depth of discharge, DoD and is related to SoC as $DoD = 1 - SoC$ [7].

Power is delivered by both the battery and the UC, and the initial SOC of the UC is not 100%. To simplify calculations, the DoD of the UC, expressed as $SoC_{iUC} - SoC_{UC}$, is converted to an equivalent DoD of the battery. This helps to linearly relate the total DoD of the battery to the distance travelled and thus find the range of the EV when the energy storing units are completely depleted. The following equations are used to calculate the battery equivalent of the UC, SoC_{eq} , and the final SoC of the battery, SoC_{final}.

$$SoC_{eq} = \frac{Q_{bat}}{cap_{bat}} \quad \text{Eq. 8} \qquad SoC_{final} = SoC_{bat} - SoC_{eq} \quad \text{Eq. 9}$$

The range, r, of the EV is calculated using the following equation

$$r = \frac{d}{1 - SoC_{final}} \quad \text{Eq. 10}$$

3.2 Metamodeling

A metamodel was used to fit a model to the data obtained through simulations. Since running even 2,000 simulations was computationally expensive, this method was used to project the performance of the vehicle for design variable combinations not directly simulated.

A Feed-forward neural network was used to fit the curve by minimizing the root squared-error of the testing data. The inputs are **x= [** n_{Bs} , n_{Bp}, n_{Cp}, n_{Cs}, L, p, N **]** and the output is the range and the values were all obtained through DOE. 70% of the data was used to train and 15% each was used to validate and test the simulation results. The model also included 10 hidden neurons. The figure below shows the regression results of metamodeling.

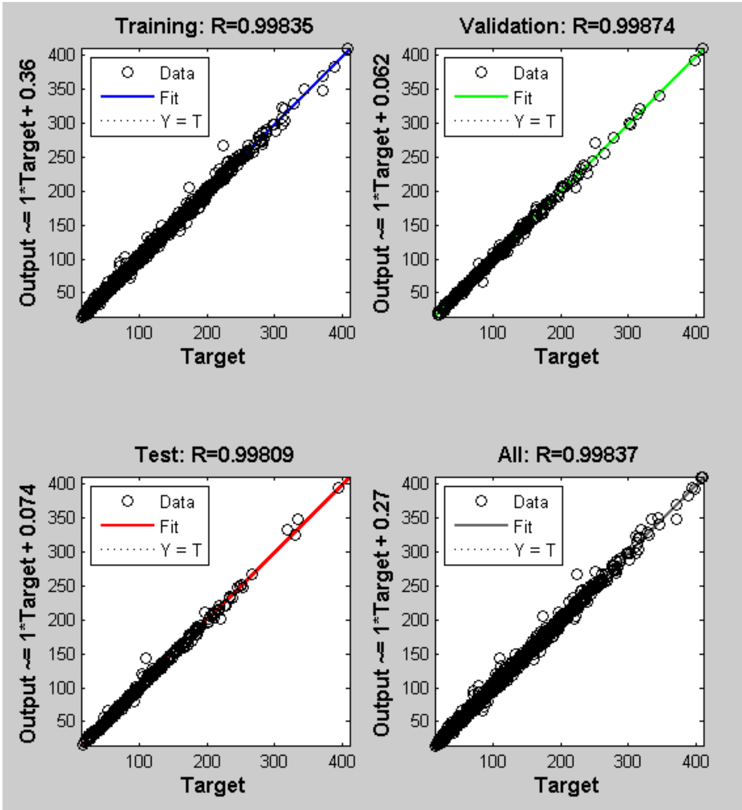

Fig. 7: As shown in the figure, the R value is close to 1 which means that the model was a good fit to the data.

3.3 Optimization Results

Based on the metamodel obtained, range is minimized in its negative null form.

x0 = [120 2 60 4 0.044 3 10]

is the set of initial values considered in the optimization code and is of the order,

x = [n_{bS} n_{bP} n_{cS} n_{cP} L p N]

The upper and lower bounds are as shown below.

LB = [50 1 50 1 1.5mH 1 3]

UB = [150 4 100 4 6.0mH 4 15]

Cost of the energy storing units is considered using a non-linear inequality equation. No other linear equality or inequality constraints are considered in this project.

Finally, a predefined function, fmincon is used to minimize the range in the negative null form. With the cost constraint being inactive, an optimal combination of design variables and the optimal range, r* of the EV were obtained as shown below.

x* = [50 4 100 4 0.00218 1 3]
r* = 598.58 mi

The same result is obtained for *C*= $8,000 and is the value for which the constraint just becomes active. It should be noted that with a given cost constraint, the solution obtained is a global minimum. The optimal solution also does not depend on the initial values. The cost constraint becomes active for *C* < $8,000 and the design becomes infeasible for *C*< $1250. The following table shows the optimal solution for varying C with a minimum of $1250.

Cost (C)	**Design Variables [n_{Bs} n_{Bp} n_{Cs} n_{Cp} L P N]**	**Range (*r*)**
$8000	[50.0 4.0 100.0 4.0 0.0022 1.0 3.0]	598.58
$7000	[50.0 4.0 100.0 3.3 0.0022 1.0 3.0]	596.57
$6000	[50.0 4.0 100.0 2.7 0.0022 1.0 3.0]	594.47
$5000	[50.0 4.0 100.0 2.0 0.0023 1.0 3.0]	592.26
$4000	[50.0 4.0 100.0 1.3 0.0023 1.0 3.0]	589.91
$3000	[50.0 3.0 100.0 1.0 0.0021 1.0 3.0]	452.75
$2000	[50.0 2.1 62.9 1.0 0.0060 2.9 3.0]	202.22
$1250	[50.0 1.0 50.0 1.0 0.0060 3.0 3.0]	89.27

Table 3: Shows the optimal range and design variables for varying cost constraint

4. DISCUSSION

Without any cost constraints, the number of UCs both in series and parallel hit the upper bounds. The number of pole pairs hits the lower bound. Since EV is simulated with EPA highway fuel economy drive cycle, the EV does not accelerate as much but rather sustains the high speed. Therefore, the low gear ratio makes sense in this case. All the parameters except the number of battery cells make sense. From the optimal combination with inactive cost constraint, the number of battery cells in series hits the lower bound and is therefore inconsistent with the rest of the design variables. The DOE simulation results show that as the number of battery cells in series decrease, the range of the EV increases and this trend is counter intuitive. Since the number of battery cells hit the lower bound, the optimal value of the range is unusually high.

From the results shown above there seems to be a discrepancy in the relationship between the number of battery cells and the range. This is especially important as the control algorithm determines the power load distribution between the battery and UC. A more robust control algorithm can greatly improve the performance of the simulation model instead of the heuristic algorithm used in this project.

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APPENDIX A

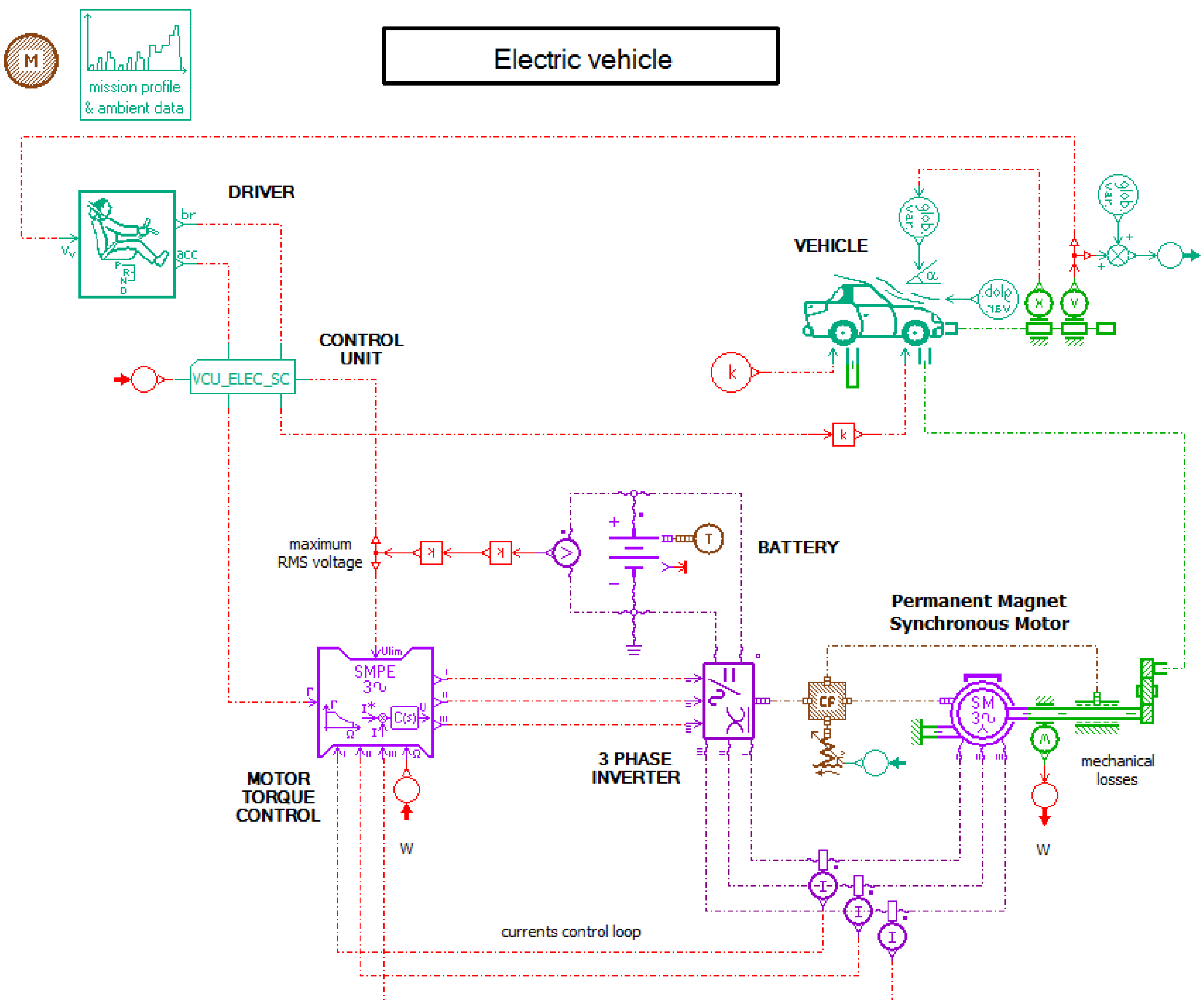

Fig. 1: Default electric vehicle model on AMESIM "Electric vehicle - Physical model of electric powertrain"

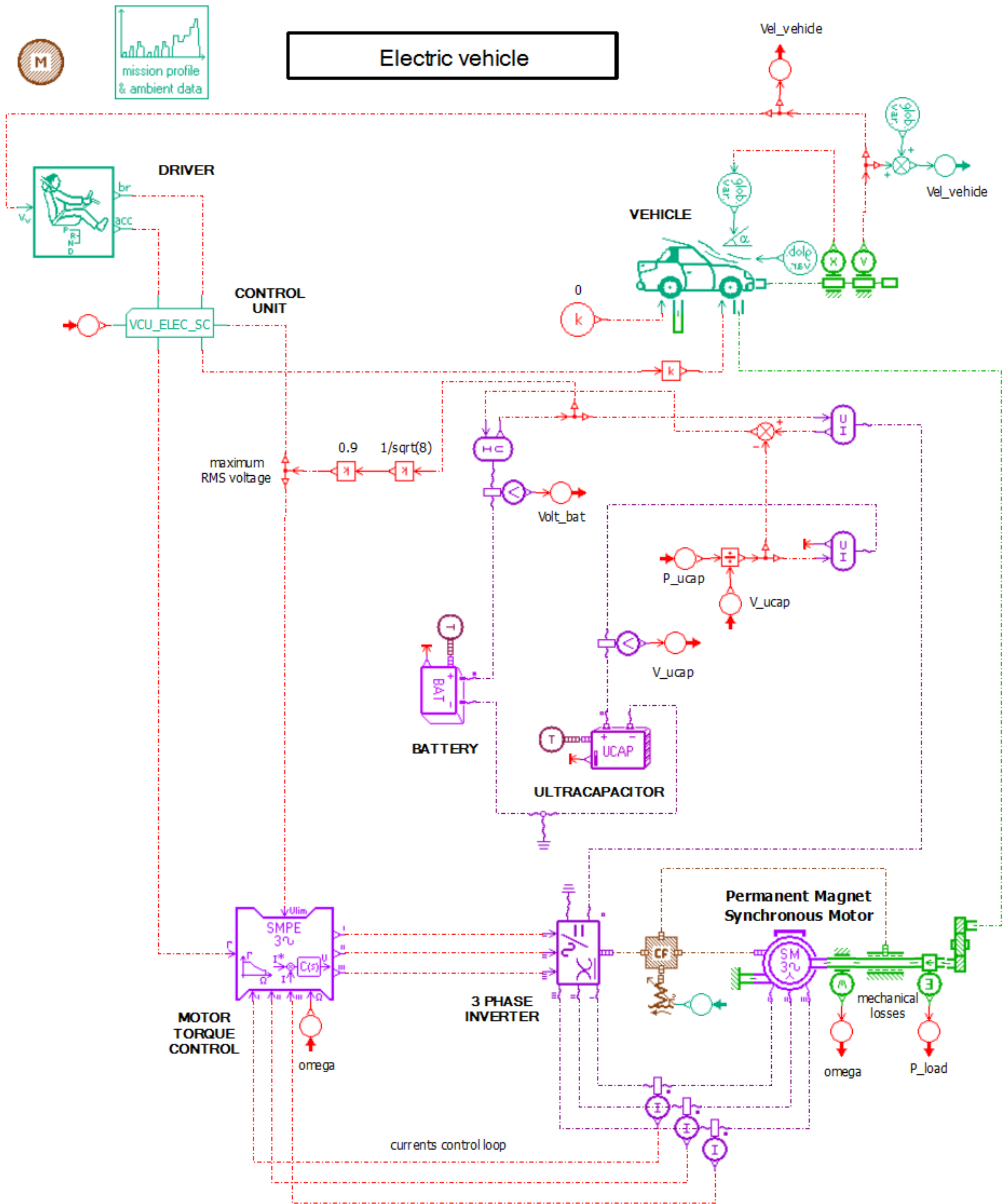

Fig 2: Modified electric vehicle model including battery and ultracapacitor on AMESIM