Uncertainty Analysis and Propagation for an Auxiliary Power Module

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***Abstract*- In modern hybrid electric vehicles (HEVs), the Auxiliary Power Module (APM) acts as the DC/DC converter which regulates the power flow between the high voltage (HV) battery and the low voltage (LV) DC bus. Optimizing the control and operation of the APM is an important component of minimizing vehicle energy consumption. Characterizing the performance of the APM requires extensive testing of APM under different operating conditions. However, in the state-of-the-art experimental validation testing using industry standard modeling practices, addressing uncertainties in the test results is not very common. A consequence of this shortcoming is the propagation of uncertainty from test to simulation, which can cause simulated results to diverge significantly from real world performance. In this paper we present test procedures and results for a Delphi Auxiliary Power Module (APM) that was installed in a 2011MY Chevrolet Volt. Experimental uncertainty in the measurand of efficiency is modeled using Scheffe confidence intervals as a function of APM output current. Uncertainty is then propagated through a vehicle fuel economy simulation to understand the role of APM experimental uncertainty in vehicle fuel economy prediction.**

I. Introduction

The introduction of Hybrid Electric Vehicles (HEVs) has resulted in various advances in both electrical and mechanical systems compared to conventional ICE vehicles [1], [2]. Some of the major additions are high voltage (HV) electric motors/generators, HV battery packs, and an Auxiliary Power Module (APM) to maintain the state of charge of the accessory battery. Typically, the modeling and simulation of the energy consumption of the abovementioned automotive sub-systems is performed using intepolated maps of experimental data [3], [4]. Unfortunately, even simulations that have undergone concerted validation efforts do not consider the effect of modeling uncertainty on the error in their simulation outputs. This study aims to demonstrate a series of experiments, models, and simulation systems that can be used to quanitfy, model, and propagate uncertainty through vehicle fuel economy simulations, using the APM and CSU EcoCAR3 vehicle as case study.

A. *Vehicle and Subsystems Description*

In this work we consider a “P2” plug-in parallel hybrid electric vehicle which was built by making extensive modifications to a 2016 Chevrolet Camaro donated by General Motors. This plug-in HEV is designed and built by the students in the university as a part of EcoCAR3, a four-year collegiate advanced vehicle technology competition sponsored by General Motors and the US Department of Energy, and managed by Argonne National Laboratory. The main objective of the EcoCAR3 program is developing technologies and systems to maximize fuel economy, minimize greenhouse gas and criteria emissions, and maintain the consumer appeal of a 2016 Chevrolet Camaro converted to a hybrid vehicle. The vehicle architecture is shown in Figure 1. The vehicle consists of a 2.4L General Motors LEA E-85 capable engine which is connected via a clutch to a through-shaft Remy HVH 250 electric motor and then to the input for the torque converter of the 8L45 transmission. The electric motor is powered by a 7x15s2p battery pack donated by A123 Systems. The basic operating parameters of these components are shown in Table1.

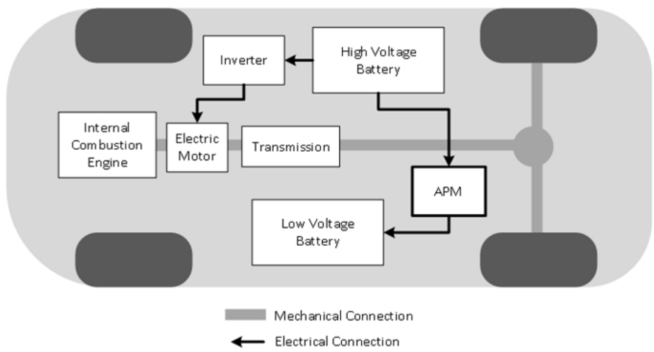

Fig. 1. Colorado State University EcoCAR3 Electronic Power System

TABLE I
COLORADO STATE UNIVERSITY ECOCAR3 VEHICLE PARAMETERS

Component	Power Ratings	Torque Ratings
2.4L LEA Ecotec internal combustion engine	135 kW @6700 rpm	233Nm @4900rpm
Remy HVH250-115 DOM electric motor	150 kW	408 Nm
GM 8L45 8-speed transmission	NA	NA
A123 7mod 15s2p battery pack (340 Vnom)	150kW	NA
Rinehart PM250 electric motor inverter	720 VDC Peak 600Arms Peak	NA
Tilton 5-5’’ Carbon-Carbon engine/motor clutch	300 kW	339 Nm

B *Auxiliary Power Module Description*

The auxiliary power module (APM) is one of the most critical components of a HEV [5]. The APM is a DC-DC converter that steps down the 350 volts from a high voltage battery to 13.5 volts, to charge the low voltage battery and to power auxiliary components. Some examples of these auxiliary components are the head/tail lights, power steering,

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air-conditioning/heater fans, audio components, windows, etc. The APM used for the EcoCAR3 project is from General Motors 2011MY Chevrolet Volt. The electrical power system of the EcoCAR3 HEV is shown in Figure 1. Table 2 describes the specifications of the Delphi APM considered in this work.

TABLE 2
AUXILLIARY POWER MODULE PARAMETERS

Parameter	Characteristic
Input Voltage	260-420 V (DC)
Output Voltage	11-15.5 V (DC)
Max Output Current	165 A
Standard Output Power	2.2 kW
Dimensions	13” x 9” x 3.5”
CAN data rate	500 kbps

II. METHODS

A Auxiliary Power Module Control Strategies

To achieve an efficient APM operation while improving the vehicle performance, two APM control strategies were tested.

In the first strategy, the output voltage from the APM is set to a constant set point of 13.5 V. This control strategy helps to maintain the state of charge of the low voltage battery and directly powers accessory components. This control strategy is static to ensure consistent performance, however it may result in the APM operating at low currents with low resulting power conversion efficiency during periods of low auxiliary system loading [6].

The second strategy seeks to increase the power conversion efficiency by turning the APM off during periods of low auxiliary system loading. The auxiliary battery in this strategy directly powers the accessory loads until its state of charge reaches a lower setpoint. The APM is turned back on when this level is reached or when the current load is sufficient to operate near maximum efficiency. This strategy is hypothesized to improve the APM performance by always running the APM at peak efficiency, however it could also increase the load power consumption when the APM is running, which would impact the overall power consumption. This strategy of “burst charging” was investigated through the development of an active APM control model, which could be contrasted with the static control strategy.

B Auxiliary Power Module Experimental Setup

Through a series of tests, the power conversion efficiency of the APM was measured in a benchop setting, using an N8924A Power Analyzer provided on loan from Keysight Technologies. First, the APM is initialized with an input DC voltage of 350 V. Then, the APM output voltage was set from a range of 12.5 V to 15.5 V. For each set point, a range of current loads were applied from 9 A to 174 A. Power conversion efficiency was measured for the different current loads allowing for the verification of the information listed in the APM user's guide. The goal of these tests was to determine the viability of the control strategies described in the proceeding section.

The overall test bench setup is illustrated in Figure 2. The APM takes high voltage input from the power supply which is then converted to low voltage, and outputted to the load supply. The input and output power of the APM is monitored by the power analyzer. All of these devices are controlled using a computer running MATLAB scripts. In Figure 3, the actual test bench is pictured. The wiring diagram for the entire setup is shown in Figure 4.

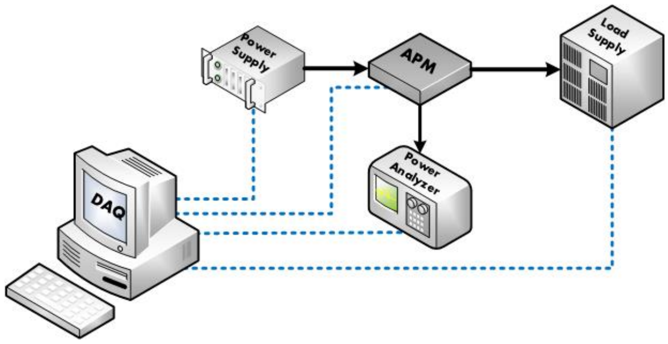


Fig. 2. Functional Diagram of Test Bench

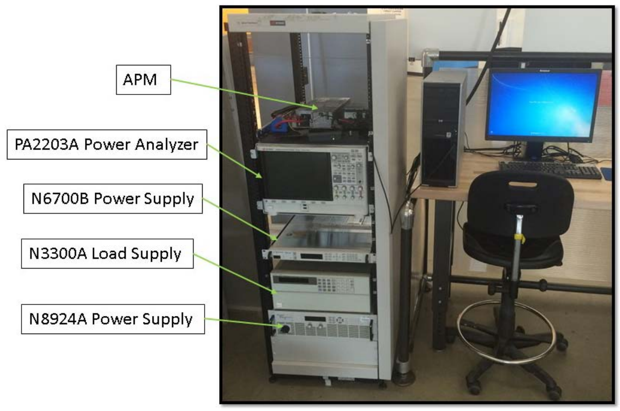


Fig. 3. Test Bench Overview

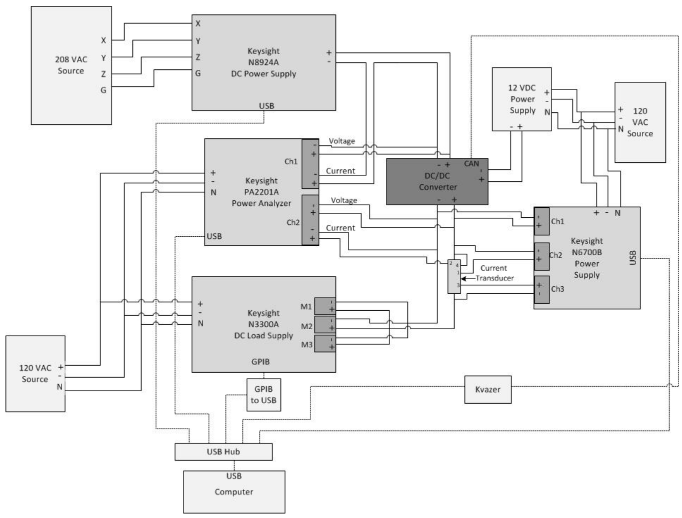


Fig. 4. Test Bench Wiring Diagram

C Experimental Methods

The APM first has a startup sequence that needs to be followed in order to have a successful startup and power conversion. After the APM initializes successfully, the validity of the first control strategy, a set point of 13.5 V was tested through a current sweep. The Keysight N3300A load mainframe was then set to request increasing current values. Starting at 9 A, the current was increased by 9 A (three amps per module on the load supply) until a current of 174 A was reached. For each current value, the efficiency was measured using the Keysight PA2203A Power Analyzer.

Next, the data to test the "burst charging" control strategy was tested by changing the APM output set point voltage. Starting at 12.5 V, current sweeps were performed as discussed above. The output voltage was set in increasing values of 0.5 V until 15.5 V were reached. These values were set using the Kvaser Leaf Light HS v2 with CAN commands. For each voltage set point, the current load was changed (9 A to 174 A) and efficiency was measured as the ratio of LV electrical output power to the HV electrical input power.

D Modeling and Simulation Methods

MATLAB's Simulink tool was used to model the EcoCAR3 vehicle fuel economy. The model consists of three main subsystems. The first is the driver subsystem which replicates the behavior of the driver using Urban Dynamometer Driving Schedule (UDDS) and FU505 drive cycles as the input traces. The second is the controller subsystem that replicates the behavior of the supervisory controller and commands various plant models under the plant subsystem. The third subsystem is the physical plant model, where the APM is one among many subsystems including the engine, motor-generator, transmission, HV battery and vehicle dynamics. The engine and motor are modeled based on experimental data stored in look up tables. For the high voltage bus system, the battery is modeled as a potential source acting through a nonlinear internal resistance. Coulomb counting is used to model battery state of charge. Open circuit voltage is modeled as a function of state of charge. All of the physical parameters of the HV battery were taken from the A123 documentation.

The low voltage bus was a simple model that included the 12V battery and the parasitic load. The 12-volt battery was modeled using the same method using data from the manufacturer. The load data was collected from the vehicle baseline evaluation tests which were based on the data taken from measuring the low voltage load from the stock vehicle at different currents and state of charge (SOC).

The APM itself is nominally represented as a 1D lookup table based on data that was provided by the manufacturer and validated internally with the bench testing described above. It calculates the load on the HV battery based on the needs of the 12 V bus. In the vehicle simulation, the APM's electrical load on the HV battery is dictated by the load requirements of the 12 V bus/battery.

Most relevant to this study is the APM control system, which manipulates the operating conditions of the APM to try and improve efficiency. A stateflow diagram is used to model

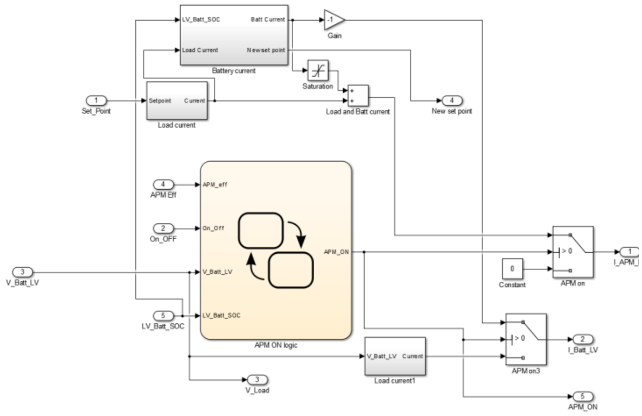


Fig. 5. APM Control Logic

and control the operation of the APM. The controller models and actuates the auxiliary bus conditions including the set point of the APM, the APM output current, the APM input current, and the auxiliary load current. Once conditions of operation are calculated, the controller block sends out the information to the plant that allows it to simulate the control strategy under test.. The layout of the controller block is shown in Figure 5.

E. Uncertainty Quantification

Scheffe's confidence intervals (SCI) are a statistical method used to model the significance levels in regression analysis accounting for multiple comparisons. For quantifying the confidence intervals around error estimations, Scheffe's confidence intervals are particularly useful when experimental data is sparse, when an underlying regression model is available, and when a continuous metric of uncertainty is desired for interpolation among datapoints.

The calculation of SCI begins with defining a regression ($\bar{y}_{\exp}(x)$) to the experimental data $y_{\exp}(x)$, as a function of APM output current, x. For this study, we considered a 6th order polynomial fit to the experimental dataset.

$$y_{\exp}(x) = \bar{y}_{\exp}(x) + \varepsilon$$

SCI defines a confidence indicator as a bounded confidence estimator of the true value of $y_{\exp}(x)$.

$$\bar{y}_{\exp}(x) - SCI(x) < y_{\exp}(x) < \bar{y}_{\exp}(x) + SCI(x)$$

At a confidence α, SCI is defined as a function of APM output current (x) using the F-statistic, as:

$$SCI(x) = s\sqrt{2 \cdot F(2, n-1, 1-\alpha)\left[\frac{1}{n} + \frac{(x-\bar{x})^2}{(n-1)s_x^{\,2}}\right]}$$

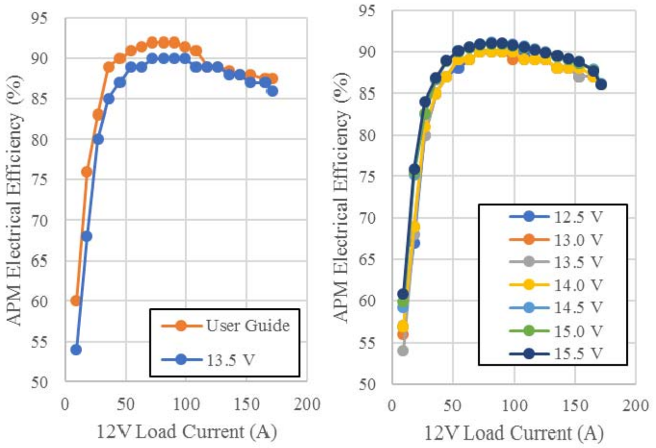
where n is the number of experimental samples, s is the standard deviation of the residuals, $\bar{x}$ is the mean of the experimental input currents, and s_x^2 is the variance of the experimental input currents.

$$s_x^{\,2} = \frac{1}{n-1}\sum_{i=1}^{n}(x_i - \bar{x})^2$$

III. Results

A Experimental Results

Figure 6(a) displays the power efficiency as a function of APM output current for the set point of 13.5 V tested on the test bench. Also displayed are the reported values provided by the Delphi APM documentation. It is expected that these curves would be very similar, as the APM's default set point is 13.5 V, matching the tested set point. The testing results show a slight difference in efficiency values. The efficiency differences between the device specifications and the measured efficiency differs up to a maximum of 8%. To better understand this difference, a set of tests were run in which the APM output voltage set point was varied. The results are presented in Figure 6(b), and it can be seen that the efficiency values closely follow the same curve. There is approximately 1% efficiency increase for APM voltage set points above 14.5 V. No significant decrease in relative efficiency is found for set points as low as 12.5V.



(a) (b)

Fig.6. (a) APM efficiency measurement compared to specifications from manufacturer, and (b) at varying output potential set points

B Vehicle Simulation Results

The default control strategy that was tested in the vehicle simulation is to keep the APM on and operating at the 13.5 V set point. Under this baseline strategy, when the vehicle is run for a long period, the 12 V battery will be discharged until its open circuit voltage is approximately 13.5V. Beyond this point, the APM is providing all of the power for the low voltage system. Only under conditions where the 12V load is greater than the current capacity of the APM, will the 12V battery provide current to the 12V bus. When the APM is set at 13.5 V the 12V power consumption averages 906W over the UDDS drive cycle.

In the simulated burst charging strategy, the battery discharges until the terminal voltage dips below 12.5 V and then the APM is turned on. The output current is high, causing the APM to generate 12V current high conversion efficiency until the SOC of the 12 V battery reaches 90%. This means that the battery will oscillate between two different SOC values as shown in the figure 7.

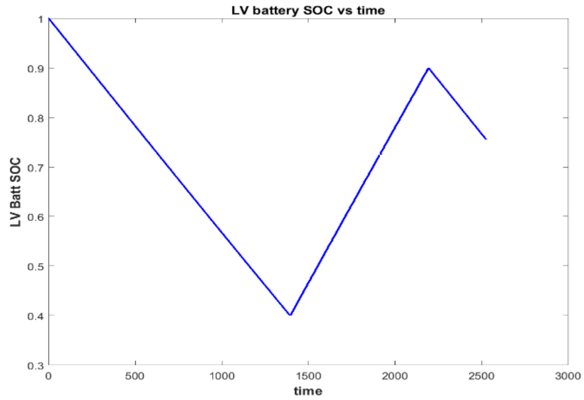
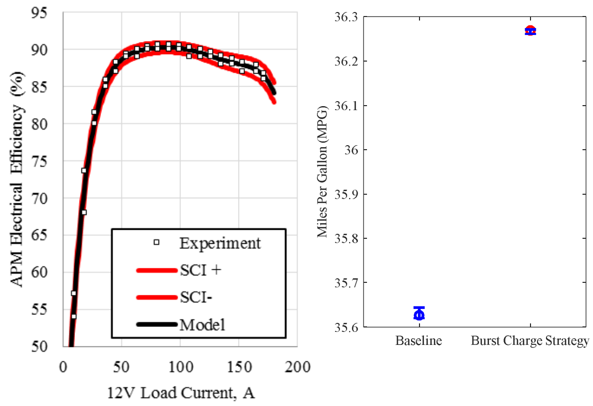


Fig.7. Simulated auxiliary battery output potential and APM state as a function of drive cycle time

C Uncertainty Quantification and Propagation

In this section, uncertainty analysis and its propagation are discussed in detail. Even in the state-of-the-art automotive testing, addressing uncertainties in test results is not very common. In this work, we performed uncertainty analysis by modeling experimental uncertainty in the measurand of APM efficiency as a function of APM output current using Scheffe confidence intervals. This uncertainty is propagated through a vehicle fuel economy simulation to demonstrate the impact of APM experimental uncertainty on vehicle fuel economy predictions. These simulations are carried out by considering the two proposed APM control strategies.

Using a 90% confidence interval for APM efficiency, the uncertainty bounds (SCI+, and SCI-) are computed considering experimental and sample uncertainties as shown in Figure 8(a).



(a) (b)

Fig. 8. (a) APM Experimental data and regression model including 90% SCI bounds, and (b) uncertainties in APM efficiency as propogated through vehicle fuel economy simulation on UDDS

The calculated uncertainty bounds for the APM efficiency are given as the input to the APM model which is placed in the full vehicle model and this uncertainty in efficiency is allowed to propagate through vehicle fuel economy simulations. In order to test this, a UDDS drive cycle input is provided to the model and both strategies one (APM always on) and two (Burst charge) for APM are tested and the output fuel economies are calculated. From figure 8(b) it can be seen that the uncertainty in APM efficiency has impacted the fuel economy calculations. Also, it can be seen that the burst charge APM control strategy has an advantage over the baseline strategy in terms of fuel economy because, in the first strategy the APM is always on compared to that of the second strategy where APM is allowed to be on only during high efficiency operations which reduces the energy consumed from the HV battery which will improve the fuel economy of the simulated vehicle.

IV. CONCLUSIONS

In this paper we have presented a detailed experimental and simulation-based analysis two different control strategies for an APM with an objective of maximizing efficiency while maintaining performance in the EcoCAR3. In the first control strategy, the APM maintained a constant output voltage of 13.5 V. In the burst charge control strategy, the APM would be turned off when not soucing > 40 A of current to the 12V load or to the low voltage battery.

The results of the efficiency bench testing show that the efficiency of the APM does vary significantly with its current output, but that the effiency is less affected by the output voltage setting. Vehicle simulation of the two control strategies demonstrate that there is a slight fuel economy improvement that is available with the "burst charge" APM control strategy. The experimental uncertainty analysis performed using the measurand of APM efficiency indicates that the experimental uncertainty associated with the measurement of the APM efficiency does not dominate the results of the control system comparison. Propagating the uncertainty associated with the experimental data demonstrates that the results of the control system analysis are robust to uncertainty in the APM performance dataset.

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