Peer-to-peer Collaborative Vehicle Health Management – the Concept and an Initial Study

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ABSTRACT

Advanced vehicle diagnostics and prognostics (D&P) technology enhances ownership experience, and reduces corporate warranty cost. D&P performance optimization requires significant algorithm tuning and a large amount of test data collection, which is resource consuming.

In this paper, we propose a novel D&P framework called Collaborative Vehicle Health Management (CVHM) to automatically optimize the D&P algorithms on a host vehicle, using the field data collected from peer vehicles encountered on the road. The carefully designed system architecture and learning algorithms enhance D&P performance without costly human intervention. The experimental results on battery remaining useful life prediction show the effectiveness of the proposed framework. This proposed framework has been implemented in a small test fleet as a proof-of-concept prototype.

1. INTRODUCTION

Diversified passenger vehicle usage leads to diversified vehicle system failure modes and aging processes. As a result, it is very challenging to achieve accurate and robust diagnostic and prognostic (D&P) performance for vehicle systems in the field. In the state-of-the-art practice of D&P algorithm development, a large amount of data has to be collected through fault injection on bench or test vehicles for diagnostics, or through accelerated ageing tests for prognostics. And a significant amount of algorithm tuning work has to be done by development engineers.

Motivated by this challenge, we propose a novel D&P framework called, Collaborative Vehicle Health Management (CVHM), where field data from peer vehicles are aggregated to automatically optimize the D&P algorithms for the host vehicle. This is an extension of the decade-long evolving research and development in the area of remote vehicle diagnostics (Millstein, 2002) (Kuschel, 2004) (Carr, 2005) (You, Krage, & Jalics, 2005) (Zoia, 2006) (Zhang, Grantt, Rychlinski, Edwards, Correia, & Wolf, 2009) (Byttner, Rögnvaldsson, Svensson, Bitar, & Chominsky, 2009). Three key enablers are needed to realize CVHM,

1. An onboard CVHM architecture that facilitates peer vehicle data aggregation, and host vehicle D&P algorithm adaptation
2. Intelligent data modeling and statistical decision making technologies that allow the extraction of fault signature, failure precursor, trending information, and other actionable knowledge to enhance the D&P performance.
3. A heterogeneous wireless communication solution that combines cellular network, and opportunistic V2V (vehicle-to-vehicle) communication to allow the exchange of large-volume data between vehicles in a cost-effective way.

In this paper, we present the latest development in the first two items above, using battery remaining useful life as the example application. The reader is referred to (Bai, Grimm, Talty, & Saraydar, 2011) for the background of item 3.

This paper is organized as follows. The proposed CVHM architecture is introduced in Section 2, followed by the development of the prognostic algorithms in Section 3. Section 4 discusses the system implementation. Section 5 presents the experimental results. Section 6 discusses future works.

2. COLLABORATIVE VEHICLE HEALTH MANAGEMENT SYSTEM ARCHITECTURE

A typical vehicle health management system architecture is illustrated in Fig. 1. Sensor information regarding particular vehicle subsystem is either directly collected by the VHM ECU that runs D&P algorithms or is transferred from other ECUs through an in-vehicle communication network. Note that, in real implementations, the VHM ECU may be implemented as a functional module within an ECU, such as a body control module (BCM), that executes control functions. The D&P module has various D&P algorithms for different targeted vehicle components or subsystems, such as battery, electrical power generation and storage (EPGS) system, fuel delivery system, etc. The D&P module processes the sensor information, and generates D&P results, including the detected anomalies, isolated faulty components, and the predicted remaining useful life (RUL) of related components. The D&P algorithms are usually developed, calibrated, and tested through a sophisticated vehicle development process. Once the vehicle is released for production, the D&P algorithms and the associated calibration values are usually fixed. If major updates on the onboard algorithms are needed, an ECU reprogramming can be done after the vehicle is usually called to a dealer service shop. Lately, the technology of remote ECU refresh is maturing, which may allow the ECU reprogramming to be done remotely through telematics connections.

The proposed CVHM system, as shown in Fig. 2, is built upon the existing VHM system architecture. The newly added V2X ECU provides the wireless communication interface in order to exchange vehicle health related data between the host vehicle and peer vehicles. V2X represents vehicle-to-vehicle or vehicle to infrastructure. The V2X ECU stores the data in an onboard database. The VHM ECU has an algorithm adaptation module and a learning algorithm library, in addition to the regular D&P module. The algorithm adaptation module makes use of appropriate learning algorithms to process the vehicle health related data stored in the onboard database in order to tune and optimize the calibration values within the D&P module.

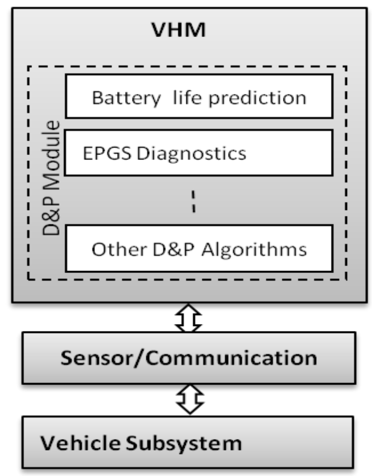


Fig. 1: A typical VHM system architecture in the state-of-the-art

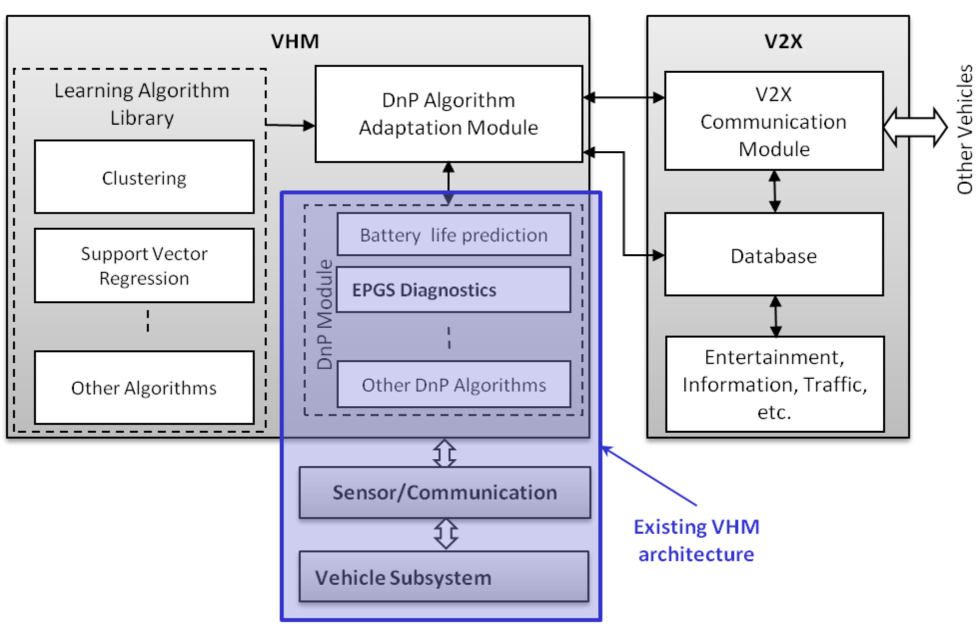


Fig. 2: Proposed CVHM system architecture

The advantage of CVHM can be understood based on the following example. A battery life prediction algorithm usually implements an ageing model that specifies how the battery internal resistance grows given the number of charge-discharge cycles. There are parameters in the ageing model that specifies the growth rate of the battery internal resistance, which is critical in battery life prediction. These parameters are typically calibrated using accelerated ageing test during the vehicle development process, and applied to across the board to all vehicles. However, it is difficult for a pre-calibrated model to account for the intrinsic diversity of usage patterns and environment impacts. The fact is that batteries for the same battery/vehicle model may have different life span that ranges from 1 year to 10+ years. At the same time, with large enough vehicle population, for any given vehicle, chance is high that there are peer vehicles with similar usage profiles that have been used for longer time, and therefore have gone further ahead in the ageing process. With CVHM, field data from these peer vehicles can be used to fine tune the growth rate in the battery ageing model, and consequently achieve higher prediction performance.

3. ALTORITHM DEVELOPEMNT

The general framework to develop model-based prognostics for remaining useful life (RUL) prediction involves the following steps.

First, one or more fault signatures are identified to characterize target system's state of health, $Z = f(\mathrm{SOH})$. Depending on applications, these fault signatures may be assessed either directly or indirectly. For example, in the application of SLI (Starting, Light, Ignition) battery life prediction, multiple fault signatures have been proposed (Zhang, Grube, Shin, & Salman, 2008) (Zhang, Grube, Shin, & Salman, 2009) (Shin & Salman, 2010). Some of them can be directly measured by onboard sensors, *e.g.*, minimum cranking voltage. Some of them can be directly calculated from other sensor measurements, *e.g.*, cranking resistance can be calculated by dV/dI, where dV and dI are voltage and current changes in the beginning of the cranking process, respectively. There are also fault signatures that cannot be directly measured, and have to be estimated as the parameters in a system model, *e.g.*, battery capacity.

The second step is to establish the failure criteria for fault signatures with respect to specific applications. That is, if $Z > Z_0$, a system failure is declared, where Z_0 is a threshold. For example, one of the main functions for SLI battery is to crank the engine. As battery ages, its SOH deteriorates, and so does its cranking capability. One of the fault signatures, cranking resistance, increases during the ageing process. When the cranking resistance reaches certain level, the engine can hardly be started. This is when a battery failure is declared. The failure criteria are highly application specific, and usually require careful calibration.

The third step is to establish a system-ageing model that specifies how the fault signatures evolve with respect to usage. That is,

$$Z = Z(L; \theta),$$

where L is a set of variables that characterize the usage profile of the target system, and θ is a set of parameters that specify the detailed relationship between the usage and the fault signature evolution.

The CVHM framework follows the above general model-based prognostics framework. The main enhancement is that the system ageing model is updated as more data is made available from peer vehicles. In the next few sections, we take battery RUL prognosis as an example application to illustrate the development and implementation of the CVHM framework.

3.1. Fault signature generation algorithms

Extensive previous research has been conducted, and multiple SLI battery fault signatures have been identified, including minimum cranking voltage, delta V, cranking power, voltage residual, and cranking resistance (Zhang, Grube, Shin, & Salman, 2008) (Zhang, Grube, Shin, & Salman, 2009) (Shin & Salman, 2010). A brief description of these fault signatures are listed Table 1. These fault signatures change along with the battery age. For instance, the cranking resistance increases in an accelerated ageing experiment, as shown in Fig. 3. It's worth noting that the battery capacity is also an effective signature. However, it is difficult to be estimated accurately online.

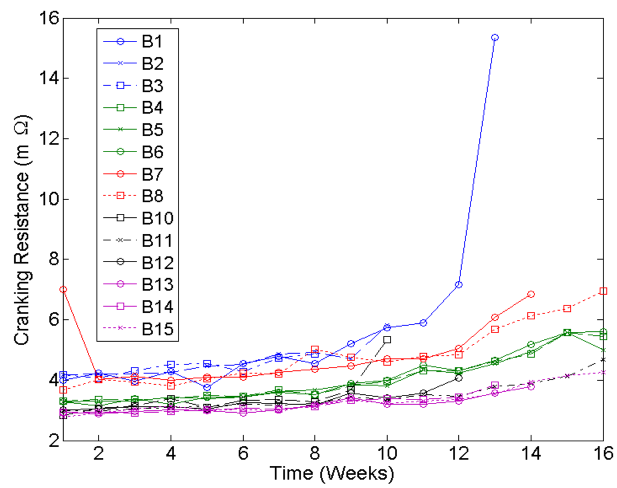


Fig. 3 Cranking resistance change during the accelerated ageing test for 14 batteries from JBI_Aging_2008 data set (battery 9 does not have data) in the conditions of 100% SOC and 25°C

Battery Fault Signatures	Formula
Minimum cranking voltage	$V_{min} = \min(V_{batt})$
Delta V: the difference between the first and second minimum voltage	$V_{delta} = V_{min1} - V_{min2}$ Where V_{min1} and V_{min2} are the first and second minimum voltages, respectively
Cranking power	$P = \int_{T}^{T+0.5} V_{batt} I_{batt} dt$ where $T = t$ when $I > 100A$
Voltage residual	$V_R = \frac{\sum_{i=1}^{n}(V_{batt}(i) - \hat{V}_{batt}(i))}{n}$ where $\hat{V}_{batt}$ is estimated by calibrated model from good batteries
Cranking resistance	$R = \frac{V_{batt0} - V_{min}}{I_{batt0} - I_{max}}$ where $I_{max} = \max(I_{batt})$

Table 1: Battery fault signatures

3.2. Prognosis algorithm with adaptation

While fault signatures indicate the current status of the fault, failure prediction requires an ageing model to depict how the fault signatures evolve as the battery ages. Multiple ageing models have been proposed in the literature. Some of them are physics-based models, considering either specific ageing mechanism of battery (Schiffer, Sauer, Bindner, Cronin, Lundsager, & Kaiser, 2007), or general ageing laws for mechanical or electro-chemical systems (Edwin, Chiang, Carter, Limthongkul, & Bishop, 2005). In reality, these models are more or less hybrids of empirical and physics-based models that have many model parameters fitted through experiments. Other models are purely data driven based on various linear or non-linear curve fitting techniques (Saha, Poll, & Christophersen, 2009). Due to the intrinsic complexity of the battery aging process, there is no clear winner in the proposed ageing models in terms of prediction accuracy. In this research, we adopted a few static parametric models, including polynomial curve fitting, exponential curve fitting, and support vector machine (Vapnik, 1998). There was not significant difference between these models in our experimental results. We present the algorithm development based on a 3rd order polynomial model due to its structural simplicity.

Each fault signature is modeled by the following equation:

$$\hat{y}(t) = p_1 t^3 + p_2 t^2 + p_3 t + p_4$$

where $\hat{y}$ is predicted fault signature value, t is the battery age in terms of service time, and p_1, p_2, p_3 and p_4 are model parameters. Since both SOC and battery temperature can affect battery fault signature, different models have to be learned for different SOC and temperatures. The battery RUL is defined as

$$RUL = \arg\min_t \, [\hat{y}(t) = y_0] - t_{current}$$

where y_0 is a predefined threshold, and $t_{current}$ is the current battery age.

As discussed in Section 2, the ageing model calibrated with accelerated ageing test may not be able to characterize the ageing process in the field. In the proposed CVHM, the ageing model is adapted using the data from peer vehicles that have gone further in the ageing process.

Let $y_H(t_j)$ be the fault signature value measured or estimated by the host vehicle at time instant t_j, where $j = 1 \ldots J$ and J is the current time index for the host vehicle. Let $p_{H,1}$, $p_{H,2}$, $p_{H,3}$ $p_{H,4}$ be the ageing model parameters maintained by host vehicle, and $p_{P_k,1}, p_{P_k,2}, p_{P_k,3}, p_{P_k,4}$ be the ageing model parameters used by peer vehicle P_k, where $k = 1 \ldots K$ and K is the number of peer vehicles. The model adaptation procedure is as follows.

1. Estimate host vehicle fault signature values using peer vehicles' ageing model parameters, which yields,

   $$\hat{y}_{H,P_k}(t_j) = p_{P_k,1} {t_j}^3 + p_{P_k,2} {t_j}^2 + p_{P_k,3} t_j + p_{P_k,4}$$

   where $\hat{y}_{H,P_k}(t_j)$ indicates the estimate of host vehicle fault signature using the ageing model from peer vehicle P_k.

2. Calculate the corresponding estimation error for the ageing model from each peer vehicle P_k as,

   $$R_{H,P_k} = \sum_{j=1}^{J} [\hat{y}_{H,P_k}(t_j) - y_H(t_j)]^2.$$

3. Pick N models with the smallest error. Without loss of generality, the corresponding peer vehicles can be represented as P_{k_1}, P_{k_2},…, P_{k_N}. In the experiment presented in this paper, N is set to 3.

4. Calculate the adjusted host vehicle fault signature values, $\bar{y}_H(t_j)$, by averaging the fault signature values based on the selected peer vehicles' ageing models,

   $$\bar{y}_H(t_j) = \frac{1}{N} \sum_{n=1}^{N} \hat{y}_{H,P_{k_n}}(t_j)$$

5. Update the host vehicle ageing model, using the adjusted fault signature values

   $$\{p_{H,1}, p_{H,2}, p_{H,3}, p_{H,4}\} = \underset{p_1,p_2,p_3,p_4}{\arg\min} \sum_{j=1}^{J} [\bar{y}_H(t_j) - \hat{y}(t_j)]^2$$

   where $\hat{y}(t_j) = p_1 {t_j}^3 + p_2 {t_j}^2 + p_3 t_j + p_4$.

The adjusted ageing model parameters $\{p_{H,1}, p_{H,2}, p_{H,3}, p_{H,4}\}$ are used for future battery RUL prediction.

4. SYSTEM IMPLEMENTATION

The proposed CVHM architecture has been implemented in a three-vehicle test fleet for the battery RUL prognosis application. To reduce the development cycle and cost, the test fleet is constructed in the way that one host vehicle implements the full CVHM architecture, and two peer vehicles implement only the V2X module. Each of the two peer vehicles maintain a database of battery D&P data from multiple batteries, which simulates the situation where data from multiple peer vehicles can be transferred to the host vehicle for D&P algorithm adaptation.

For the host vehicle prototype implementation, there are three major hardware components as shown in Fig. 4. The first one is a dSpace® MicroAutoBox (MAB) that has direct connection with the sensors on the battery. It employs the functions of data acquisition, signal pre-processing, and fault signature generation. During each vehicle cranking process, the MAB generates multiple battery-status related parameters, including battery temperature, SOC, cranking resistance, minimum cranking voltage, cranking powering, delta V, voltage residual.

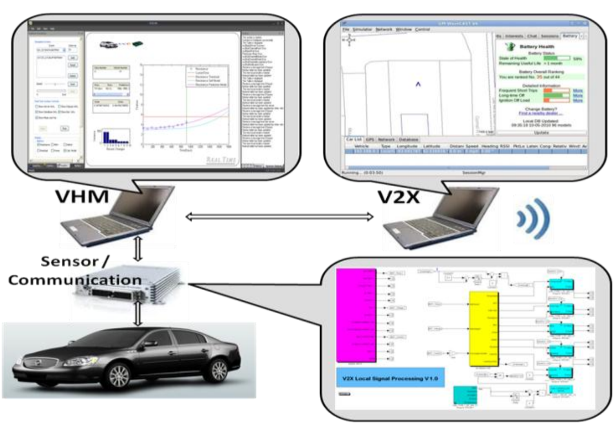


Fig. 4: Overview of system Implementation

The second major hardware component is a VHM laptop (an HP® 8440w laptop with Microsoft® Windows XP) that connects with the MAB through a Vector® CANCaseXL. The VHM laptop implements a VHM module that runs the adaptive D&P algorithms to predict battery RUL. The implementation of VHM module involves multiple operations, including the CAN (Control Area Network) communication with MAB, the D&P algorithms, the database manipulations, the communication with the V2X laptop, and a graphical interface for development users to conduct debugging and demonstration. A C++/MATLAB mixed programming technique is used to effectively accommodate different operation needs.

The third major hardware component is a V2X communication laptop (an HP® Compaq 6910P with the OS of Linux Ubuntu 10) that communicates with the VHM laptop through TCP/IP based connection. The V2X laptop implements the V2X module that interacts with peer vehicles and infrastructure through a wireless communication to exchange data. It maintains a MySQL® database server to organize the data as well as manage the retrieval requests from the VHM module. The details on this part of implementation will be covered in a forthcoming publication. The V2X laptop also serves as the driver interface module to provide battery health information to the end user.

5. EXPERIMENTAL RESULTS

The CVHM system has been validated using the JBI_Aging_2008 data set. In this data collection effort, 15 batteries from different suppliers were aged from fresh to the end of life through an accelerated ageing process. The battery age varies from 8 to 16 weeks. During the ageing process, weekly cranking tests were conducted on a test vehicle for each battery after it was conditioned to 100% state of charge (SOC) and the temperature of 25°C. Battery current, battery voltage, and engine RPM were collected during cranking. After data cleaning, there are totally 1710 cranking data files that have adequate data for 14 batteries (battery 9 has no data). Table 2 summarizes the battery information from this data set.

Battery ID	Indices of Battery Types	Accelerated Ageing Life (weeks)
1	I	13
2		10
3		8
4	II	16
5		16
6		16
7	III	14
8		16
9		No Data
10	IV	10
11		16
12		12
13	V	14
14		13
15		16

Table 2: Summary of JBI_Aging_2008 data set

5.1. Fault signature

Fig. 5 shows the fault signatures of the batteries in the JBI_Aging_2008 dataset, including minimum cranking voltage, delta V, cranking power, voltage residual, and cranking resistance. Among these fault signatures, cranking resistance appears to be better SOH indicators than others, due to its consistency and monotonic correlation with the battery age. Therefore, we selected the cranking resistance as the fault signature in the rest of the experiments.

5.2. Remaining useful life (RUL) prediction

In order to evaluate CVHM-based battery RUL prediction, we conducted the experiment as follows. We randomly selected a battery, battery #6, from JBI_Ageing_2008 dataset, and loaded the cranking data from battery #6 to the local database on the host vehicle. At each ignition on, the cranking data at different battery age was fed to the VHM module in order to simulate the battery ageing process. The data from another randomly selected battery, battery #2, was used to calibrate the initial battery ageing model as described in Section 3.2. The data from the remaining 12 batteries were loaded in the two peer vehicles in order to simulate the fact that the peer vehicle population carries different batteries, and has gone through the full battery ageing process on those batteries. The host vehicle experienced multiple encounters with the peer vehicles, during which the battery data stored in peer vehicles were transferred to the host vehicle through V2V communication. The host vehicle used the newly acquired data to update the ageing model and the battery RUL prediction.

Fig. 6 illustrates the battery RUL prediction results during one particular ignition cycle. At this particular ignition cycle, the host vehicle battery has been in service for 540 days, assuming each week of accelerated ageing corresponding to about 90 days of real-world driving. The cranking resistance has increased from the initial value, but is still significantly lower than the end of life threshold indicated by the black horizontal line in Fig. 6. The initially calibrated ageing model, as shown by the blue line in Fig. 6, predicts the RUL is about 250 days, since the cranking resistance is predicted to pass the threshold in about 250 days. This prediction is very different from the actual cranking resistance data that are shown by the black cycles. At the same time, the host vehicle has access to the data from peer vehicles' batteries, of which the data from nearest neighbors are shown by the green crosses in Fig. 6. Following the model adjustment procedure presented in Section 3.2, an updated battery ageing model is obtained, and shown by the green line in Fig. 6. The updated ageing model traces the actual cranking resistance very well, and provides a fairly accurate RUL prediction. Table 3 presents more detailed RUL prediction results. After the first encounter between host vehicle and a peer vehicle, the peer vehicle transferred the data of four batteries to the host vehicle. The updated ageing model had an RUL prediction error of 339 days. As more battery data was transferred, the RUL prediction error of the updated ageing model continuously reduced. So was the standard deviation of the prediction error, which suggests that the prediction is increasingly reliable.

6. DISCUSSIONS AND FUTURE WORKS

6.1. Preliminary penetration analysis

One of the key factors to the success of the CVHM framework is the access to peer vehicles' data. This is especially challenging in the early phase of CVHM deployment when the penetration of the CVHM system is low. We will try to answer the question that how many peer vehicles are needed to achieve specific RUL prediction performance.

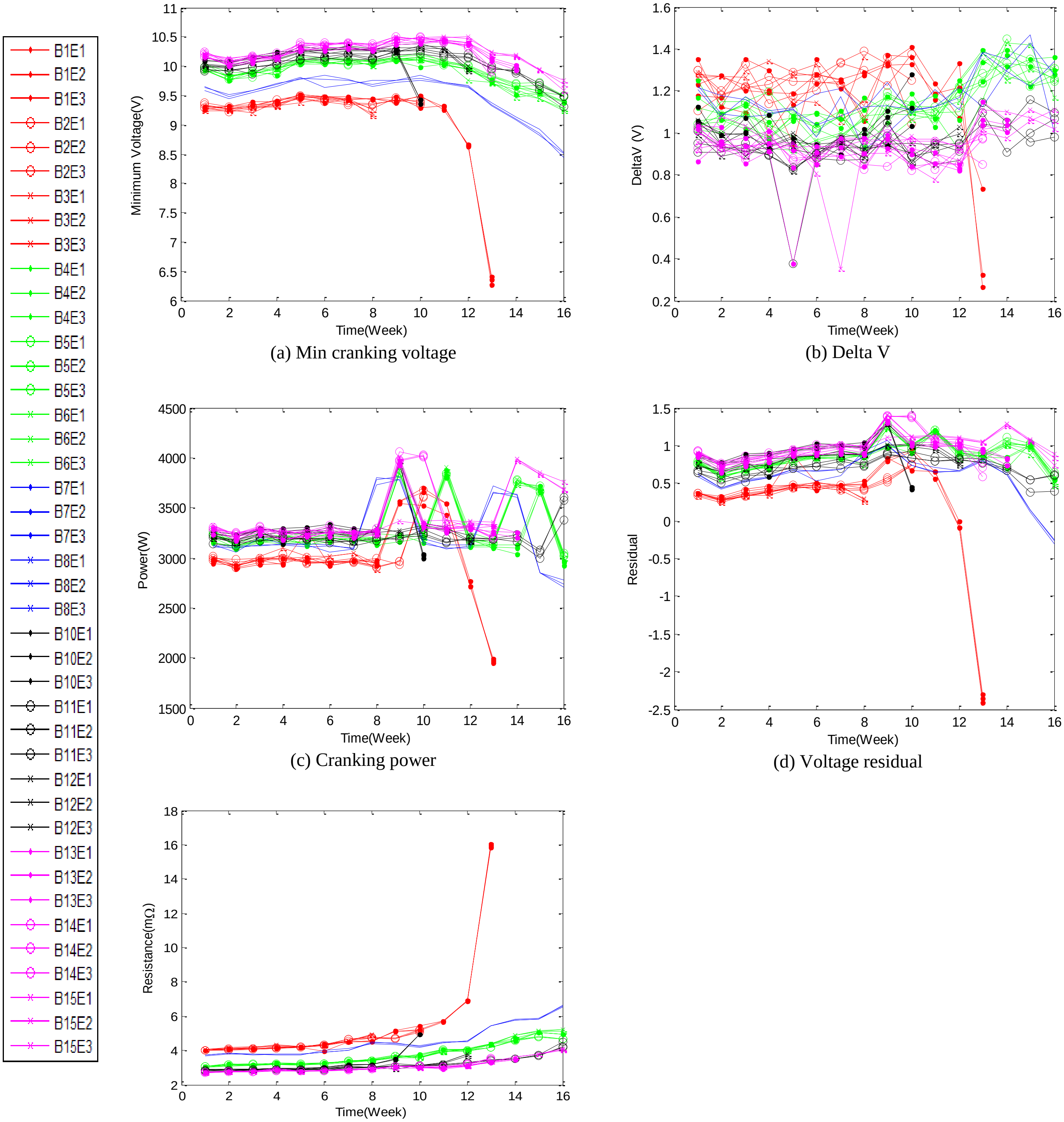
The performance of RUL prediction can be measured by the accuracy and the precision (Vachtsevanos, Lewis, Roemer, Hess, & Wu, 2006). The accuracy specifies the difference between predicted value and the actual value. The precision specifies the spread of the predicted values. Many different metrics have been proposed (Saxena, et al., 2008). In this paper, we define the RUL prediction accuracy as $E(t_{pf} - t_{af,h})$, which is the expectation of the error between the predicted battery RUL, t_{pf} , and the actual RUL of the host vehicle battery, $t_{a,f,h}$. And the precision is defined as $\sigma(t_{pf} - t_{af,h})$, which is the standard deviation of the error.

With the adaptive prognostics proposed in Section 3.2, t_{pf} is obtained by the sample mean of the battery RUL from selected peer vehicles. That is $t_{pf} = \frac{1}{n}\sum_{i=1}^{n} t_{af,i}$, where $t_{af,i}$ is the actual battery RUL for selected peer vehicle *i*. Assuming the batteries of the host vehicle and the *selected* peer vehicles have the same ageing behavior, $t_{af,i}$ and $t_{af,h}$ follow the independent and identical distribution (i.i.d.) with the expectation E_0 and the standard deviation σ_0 , According to (Spiegel, Schiller, & Srinivasan, 2009), we have,

$$E(t_{pf} - t_{af,h}) = E\left(\frac{1}{n}\sum_{i=1}^{n} t_{af,i} - t_{af,h}\right) = \frac{1}{n}\sum_{i=1}^{n} E(t_{af,i}) - E(t_{af,h}) = \frac{1}{n}\sum_{i=1}^{n} E_0 - E_0 = 0,$$

and

$$\sigma(t_{pf} - t_{af,h}) = \sigma\left(\frac{1}{n}\sum_{i=1}^{n} t_{af,i} - t_{af,h}\right) = \sqrt{Var\left(\frac{1}{n}\sum_{i=1}^{n} t_{af,i}\right) + Var(t_{af,h})} = \frac{\sqrt{n+1}}{n}\sigma_0.$$



(a) Min cranking voltage

(b) Delta V

(c) Cranking power

(d) Voltage residual

(e) Cranking resistance

Fig. 5: Fault signatures at 100% SOC and 25C for batteries in JBI_Ageing_2008 data set. Same battery types share the same color in the figure.

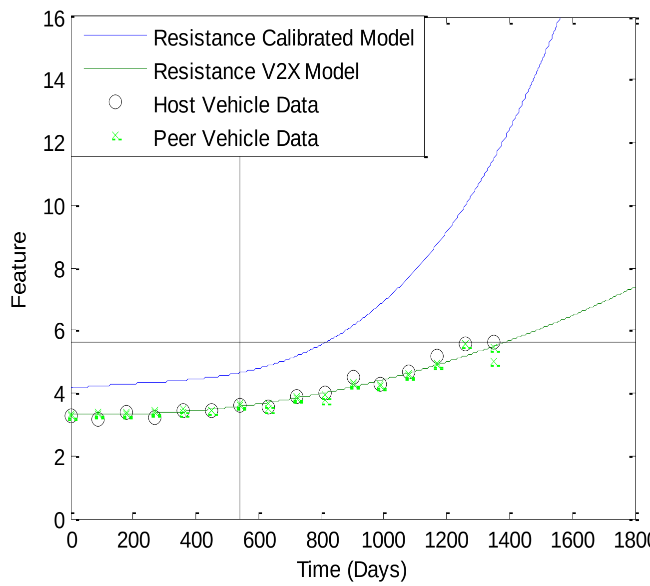


Fig. 6: Comparison of battery RUL prediction with pre-calibrated model and adaptive model

Number of peer vehicles' batteries	4	8	12	13
Actual RUL (Days) – Ground truth	964	964	964	964
Predicted RUL (Days)	625	1143	1040	992
Error (Days)	-339	+179	+76	-28
Sample Standard Deviation (Days)	460	220	139	71

Table 3: The relationship between the prediction power and the number of batteries whose data are transferred from peer vehicles. The results are based on the JBI_Aging_2008 dataset. Note that the prediction error and standard deviation are relatively high, due to the fact that the batteries in the JBI_Aging_2008 dataset represent 5 totally different battery types. In real applications, data from same battery type is available, and the prediction performance will be better.

In other words, under the i.i.d. assumption, the RUL estimation will have zero expected error, which is very desirable. And the error spread of the CVHM-based prediction is reduced by a factor of $\frac{\sqrt{n+1}}{n}$ from the single vehicle battery RUL prediction, which shows why the CVHM framework enhances the prediction performance.

If we further assume the battery RUL distribution is normal, the prediction error will be within the error bound $[-\Delta, +\Delta]$, where $\Delta = \Phi^{-1}(1-\frac{\alpha}{2})\sigma\left(t_{pf} - t_{af,h}\right)$ at the confidence level α, and Φ is the cumulative normal distribution function. To achieve a specific RUL error bound Δ_0, we need to have $\Delta \leq \Delta_0$, which yields that the minimum number of selected peer vehicles is $[\Phi^{-1}(1-\frac{\alpha}{2})\sigma_0/\Delta_0]^2$. To simplify the calculation, we approximate $\frac{\sqrt{n+1}}{n}$ with $\frac{1}{\sqrt{n}}$.

Here is a hypothetic example. Suppose the standard deviation of battery life for the whole population of a certain battery type is 35 days, *i.e.*, $\sigma_0 = 35$. This means that the actual life of most of this battery population (95% if an normal distribution is assumed) fails within a range of +/-70 days around the average battery life, which is a fairly wide spread. To achieve the RUL prediction error bound of +/- 7 days (Δ_0= 7) with 95% confidence ($\alpha = 95\%$), the least number of selected peer vehicles is 100, according to the analysis above. As a comparison, Table 4 shows the number of potential peer vehicles with similar ageing behavior under different CVHM penetration rates.

Vehicle population (within a Metro area)	**Penetration of CVHM systems**	**Percentage of selected peer vehicles (with similar ageing behavior)**	**No. of selected peer vehicles**
200 K	0.5%	5%	50
200 K	1%	5%	100
200 K	2%	5%	200

Table 4: Number of potential peer vehicles with different CVHM penetration rate

6.2. Sophisticated ageing model

In a CVHM system, the ageing model is important for system efficiency and accuracy. As an initial attempt, we explored a few static parametric models in this project, such as 3rd order polynomial model, exponential model, and support vector machine, and obtained satisfactory experimental results. In the future, we plan to further investigate other physics-based models and pure data-driven models. We are currently in the process of developing a physics-based Lead-Acid battery ageing model. It models various aspect of battery behavior including electrical, thermal, and ageing. It covers major battery failure modes such as corrosion, sulfation, and water loss. It also models a very particular phenomenon in flooded Lead Acid batteries, called acid stratification, which is not a battery failure mode itself, but accelerates the battery ageing.

System ageing depends on not only the intrinsic system property but also on its usage. Therefore, system RUL prediction has to be able to capture and predict timedependent usage patterns, which is usually very difficult to do with physics-based models. On the data-driven side, time-series models (Brockwell & Davis, 1991) (Rasmussen & Williams, 2006) are among other candidate methods we are considering to capture more complex trends in field data.

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