Proceedings of the
2007 IEEE Intelligent Vehicles Symposium
Istanbul, Turkey, June 13-15, 2007

An Intelligent Diagnostic/Prognostic Framework for Automotive Electrical Systems

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Abstract—**Automotive systems are becoming increasingly dependent on electrical components, computer control, and sensors. It has become extremely critical to detect faults in the electrical system and predict the remaining useful life of failing components. This paper introduces an integrated methodology for monitoring, modeling, data processing, fault diagnosis, and failure prognosis of critical electrical components such as the battery. The enabling technologies include signal processing, sensor selection and placement, selection and extraction of optimum condition indicators, and accurate fault diagnosis and failure prognosis algorithms that are based on both the physics of failure models and Bayesian estimation methods. The proposed architecture is implementable on-board an Electronic Control Unit (ECU) requiring minimum computational resources. Potential benefits include reduction in maintenance costs, improved asset reliability and availability and longer life of critical components.**

I. Introduction

INCREASED complexity and criticality of the electrical system of modern day vehicles has resulted in a paradigm shift in the manner used to monitor, maintain, and repair critical equipment and processes on-board ground vehicles. Instead of the traditional breakdown or scheduled maintenance, on-line key condition indicators are monitored and equipment is maintained on the basis of their condition only. These condition indicators (if utilized by effective diagnosis/prognosis algorithms) can assist to detect, identify, and predict the evolution in time of potentially detrimental fault conditions for a typical automotive electrical system. This would not only assist the maintenance personnel in troubleshooting, but also prevent roadside breakdowns by giving a pre-warning for critical failures. This logistic support concept, often referred to as condition-based maintenance (CBM), includes prognostics and health management capabilities (PHM) as key enablers.

Diagnostic capabilities traditionally have been applied after the initial fault detection and before failure of a system, component or subcomponent. More recent intelligent diagnostic technologies are enabling detections to be made at incipient stages of the fault condition. This gap between the early detection of incipient faults and progression to actual system (or component) failure is the realm of prognostics technologies [1]. Prognosis is the key component of any condition-based maintenance/prognostic health management (CBM/PHM) system. In that sense, a novel approach for accurate and precise prognosis based on particle filtering and learning strategies is proposed hereby, and applied for failure prognosis of vehicle electrical system components. It avoids both linearity and Gaussian noise assumptions of Kalman filtering, and it provides a robust framework for long-term prognosis while accounting effectively for uncertainties [2].

This paper focuses on fault diagnosis and failure prognosis of vehicle Electrical Power Generation and Storage (EPGS), system which includes the battery, generator, electrical loads, and voltage controller. The system is modeled in SABER – a simulation platform widely used for electric systems. A Failure Modes and Effects Criticality Analysis (FMECA) is conducted to identify critical failure modes of the electrical system. Battery grid corrosion is presented as an instance of one of the failure modes focused on in this paper. These faults are seeded in the modeled system in SABER and fault data under various conditions are recorded. The data are analyzed to obtain robust feature/condition indicators, and diagnostic algorithms are developed using those features. Finally a particle filter approach is used to predict the time evolution of fault condition based on typical automobile usage pattern and stress factors such as temperature; subsequently, the probability density function of the time-to-failure (TTF) is determined for a given failure mode.

II. Diagnosis/Prognosis Methodology for Vehicle EPGS System

A vehicle Electrical Power Generation and Storage (EPGS) system consists of the battery, generator, electrical loads, and controller as shown in Fig. 1. Electrically controlled and powered systems for braking, steering and stabilization need a reliable supply of electric energy. This system is becoming even more critical with the advent of hybrid and electrical vehicle technologies, thus making the

Manuscript received January 29, 2007.
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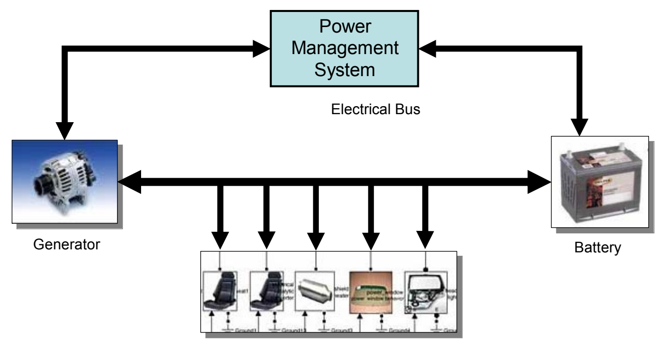

Fig. 1. Vehicle Electrical Power Generation and Storage (EPGS) System simulated in SABER

EPGS system a prime candidate for the application of condition-based-maintenance (CBM) concepts.

SABER is a well known simulation platform within the Automotive/Aviation engineering field because of its rich component library, its ability to simulate mixed (electrical, mechanical, electrochemical, etc.) systems, and complex interconnects. Thus, the vehicle EPGS system was modeled in SABER and faults were seeded in the modeled system. Simulations were run and data were collected for various operating conditions and different levels of faults. The data was then exported to a MATLAB environment, analyzed to extract features/condition indicators, and finally, diagnostic algorithms were developed for each failure mode. The receiver operating characteristics (ROC) method was used as performance metric of diagnostic algorithms. Failure prognosis framework was based on particle-filtering approach that predicts time evolution of fault growth. Fig. 2 shows the architecture for the methodology employed to design and analyze the diagnosis/prognosis algorithms for vehicle EPGS system.

Based on the FMECA study of the system, a number of critical failure modes were selected for further analysis. Among the selected failure modes, battery grid corrosion is presented as a prototypical example.

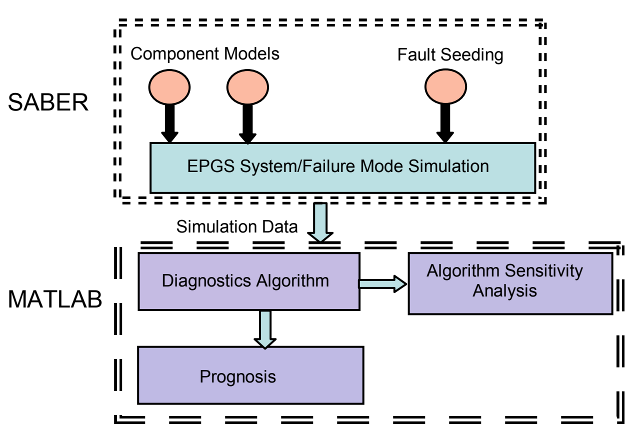

Fig. 2. Architecture for the development of diagnosis/prognosis algorithm for vehicle EPGS system using SABER as a virtual test bed

III. BATTERY GRID CORROSION DIAGNOSTIC ALGORITHM

A. Algorithm development procedure

Grid corrosion is a common failure mode for lead-acid-batteries in automobiles [3]. It results in increased real impedance, i.e., increased internal resistance of the battery [4]. Due to the slow nature of this fault growth, it is an ideal component of an automotive electrical system for the development and application of the condition-based-maintenance (CBM) concept. To model this progressive failure mode, a resistor was placed in series with the battery model in SABER and different levels of failure severity were modeled as the resistance was increased from 1 to 9 mΩ. One crucial observation in these early simulations was that the effect of the battery internal resistance was most clearly evident during transient events, such as load start-times and load end-times. Based on this, a study was conducted during engine cranking. The focus on the start-up process is advantageous because the battery and starter motor are nearly isolated from other aspects of the power generation, control, and load components during this short time interval. Under a typical cranking load profile [5], simulations were run for batteries with 4 different state of charge (SOC): 70%, 75%, 80% and 85% (all at a temperature of 25^{O} C). Simulations were run for 6 different levels of increased resistance: 0 mΩ (ok), 1mΩ, 3mΩ, 5mΩ, 7mΩ and 9mΩ. For each simulation, the following parameters were recorded:

i) Battery voltage (V_{bec})
ii) Battery current (I_{batt})

Fig. 3 shows the battery voltage for a battery at 70% SOC for six levels of fault condition

By analyzing the simulation results, a scalar feature was developed based on the time interval immediately after

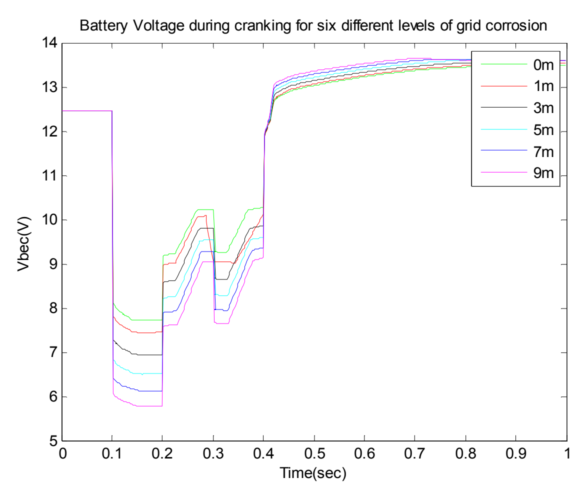

Fig. 3. Battery voltage during engine cranking for a battery with various levels of grid corrosion resistance

cranking begins. This feature is the energy flow observed at the battery terminals during the engine cranking; i.e., $E = \int_0^1 V_{BEC} I_{BEC} \, dt$.

This procedure was repeated with initial battery SOCs of 75%, 80% and 85%, with the result shown in Fig. 4.

This figure indicates that a clear one-to-one correspondence exists between the extracted feature and the corrosion resistance of the battery. Therefore, by calculating the feature value during cranking, it is possible to determine the corrosion resistance and, hence, the battery's state of health (SOH). The entire procedure can be thought of as a "virtual sensor" for the battery internal resistance.

The implications of this study are crucial to the development of a diagnostic/prognostic algorithm for battery health. Based on such a characterization, it is straightforward to invert the functional relationships shown in Fig. 4 so that the internal resistance could be inferred from both the measured energy feature – with the knowledge of battery state of charge (SOC) – and temperature as shown in the block diagram of Fig. 5. Hence, it would be possible at each starting episode to get a reading of battery internal resistance and to track this parameter over time. Furthermore, the growth of this parameter could be correlated with various stress factors such as temperature, degree of overcharge/undercharge, amount of time that the battery is at low SOC, frequency of engine on/off's per day, etc. This would allow adaptation of the model over time. This in turn forms the basis for accurate prognosis of the remaining useful life of the battery.

The developed algorithm acts as a virtual sensor for the added internal resistance of the battery, based on measurement of voltage and current drawn from battery during cranking. The algorithm assumes that the nominal current drawn by the starter motor during cranking is known.

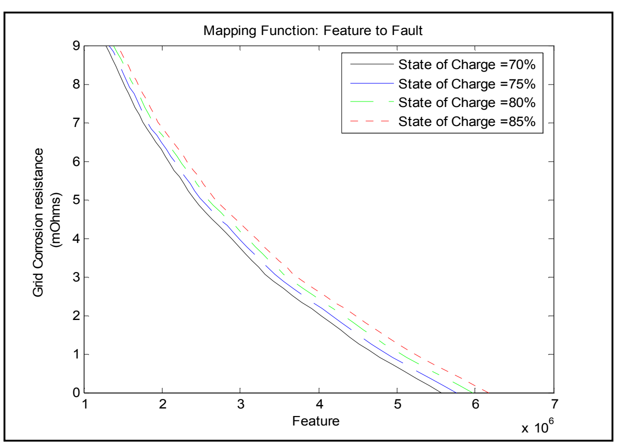

Fig. 4. Plot of feature (E) vs. corrosion resistance for battery at various values for SOC at 25 C.

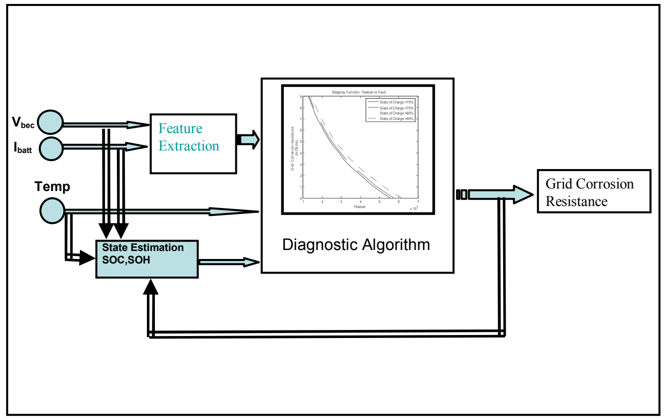

Fig. 5. Block diagram of the diagnostic algorithm using the energy feature obtained during engine cranking

This is a strong assumption since the cranking current depends on several other factors. For practical implementation of the algorithm, this assumption would require further investigation.

Another assumption is that the initial SOC of the battery is known. This is reasonable since the SOC of the battery is highly correlated with the Open Circuit Voltage [6] of the battery during idle times of the day. Any error in the initial SOC estimate would introduce some error into the SOH estimation. However, it must be noted that each time the car engine is started, another estimate of the internal resistance is obtained. Since the SOH of the battery is a relatively slow and monotonic function of time, improved estimates of the actual battery corrosion resistance are possible by averaging. As would be discussed in the following sections of the paper, a particle filter algorithm can be used not only to improve the present estimate of the internal resistance, but to predict future values.

B. *Algorithm Performance Evaluation*

In order to evaluate the performance of the developed diagnostic technique, it was tested under noisy measurements. Both the measurements used to extract the features "Battery Voltage" and "Battery Current" are assumed to be corrupted by additive white Gaussian noise (AWGN), with several signal-to-noise ratios (SNRs). Then, the feature is calculated for these noisy measurements and the result is used to estimate the corrosion resistance of the battery by employing the diagnostic algorithm shown in Fig. 5. For each set of conditions (initial SOC, corrosion resistance, SNR and temperature), a Monte Carlo procedure using 3000 noise records is conducted, generating 3000 predicted values for the internal resistance. Through this procedure, a probability density function (pdf) of the measured corrosion resistance is obtained for each set of conditions. Fig. 6 shows an example of such a pdf obtained for various levels of grid corrosion for an SOC of 80% and

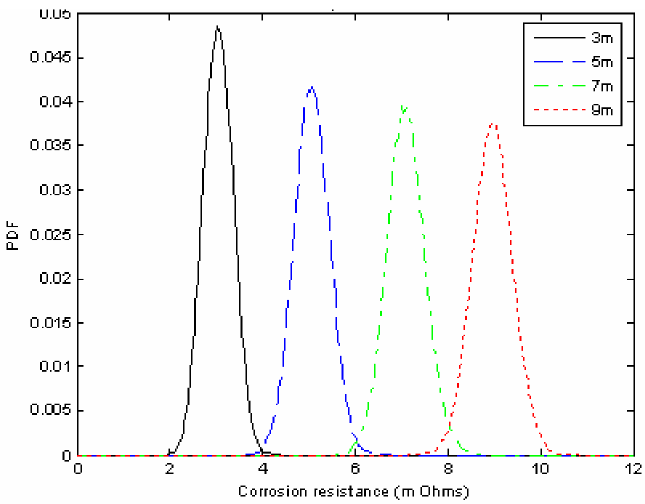

Fig. 6. Corrosion resistance probability density function (pdf) obtained with noisy measurements (battery voltage SNR= 40 dB, battery current SNR= 40 dB) for a battery with 80% SOC at 25 C.

SNR for both voltage and current of 40 dB at 25 C^{o}.

Research was conducted to determine if noise in the voltage signal was more (or less) important than noise in the current signal. From that study, it was concluded that the algorithm is more sensitive to voltage measurement noise than current measurement noise. Fig. 7a and 7b show the effect of increase in voltage sensor noise and the increase in current sensor noise, respectively.

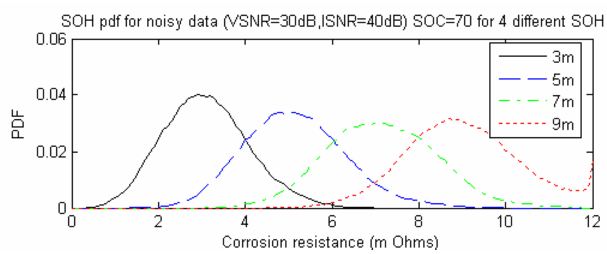

Fig. 7a. Corrosion resistance probability density function (pdf) obtained with noisy measurements (battery voltage SNR= 30 dB, battery current SNR= 40 dB) for a battery with 80% SOC at 25 C.

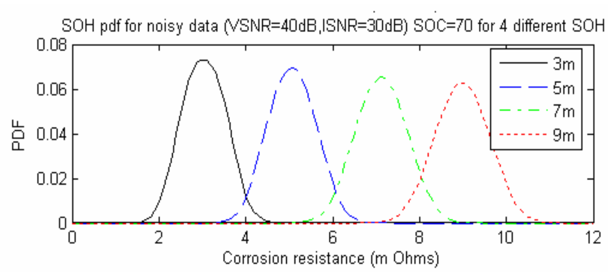

Fig. 7b. Corrosion resistance probability density function (pdf) obtained with noisy measurements (battery voltage SNR= 40 dB, battery current SNR= 30 dB) for a battery with 80% SOC at 25 C.

IV. A PARTICLE FILTER FRAMEWORK FOR PROGNOSIS

Prognosis is the key component of a condition-based maintenance/prognostic health management (CBM/PHM) system. In this particular case, a particle filtering method for prognosis of the battery grid corrosion has been used.

A. General background on particle filtering

Prognosis, or the long-term prediction of a failure condition, is based on both an accurate estimation of the current state and a model describing the fault progression. If the incipient failure is detected and isolated at the early stages of the fault initiation, it is reasonable to assume that sensor data will be available for a certain time window allowing for corrective measures to be taken, i.e., improvements in model parameter estimates so that prognosis will provide accurate and precise prediction of the time-to-failure (TTF). At the end of the observation window, the prediction outcome is passed on to the user (operator, maintainer) and additional adjustments are no longer feasible since a strong corrective action must be taken to avoid a catastrophic event.

Particle Filtering is especially useful when dealing with difficult nonlinear and/or non-Gaussian problems, such as in the case of Prognosis [2]. Compared to classical Monte Carlo methods, sequential importance sampling enables Particle Filtering to reduce the number of samples required to approximate the distributions with necessary precision, and makes it a faster and more computationally efficient approach, than Monte Carlo simulation. This is of particular benefit in diagnosis and prognosis of complex dynamic systems, because of the nonlinear nature and ambiguity inherent to the system when operating under fault conditions. In addition, particle filtering allows information from multiple measurement sources to be fused in a principled manner, something that is of paramount importance in fault detection schemes.

The underlying principle of the methodology is the approximation of the conditional state probability distribution $p(z_k/x_k)$ by a swarm of points called "particles" (samples from the space of the unknowns) containing a set of weights representing discrete probability masses. Particles can be easily generated and recursively updated [7] given a nonlinear process model (1) (which describes the evolution in time of the system under analysis), a measurement model (2), a set of available measurements $z_{1:k} = (z_1, \ldots, z_k)$ and an initial estimation for the state pdf, $p(x_o)$.

$$x_k = f_k(x_{k-1}, \omega_k) \quad \leftrightarrow \quad p(x_k \mid x_{k-1}) \tag{1}$$

$$z_k = h_k(x_k, \upsilon_k) \quad \leftrightarrow \quad p(z_k \mid x_k) \tag{2}$$

As in every Bayesian estimation problem, the estimation process can be achieved in two main steps, namely prediction and filtering. Prediction uses both the knowledge of the previous state estimate and the process model to generate the *a priori* state pdf estimate for the next time instant, as it is shown in the expression below [8]:

$$p(x_k \mid z_{1:k-1}) = \int p(x_k \mid x_{k-1}) p(x_{k-1} \mid z_{1:k-1})\, dx_{k-1} \tag{3}$$

On the other hand, the Filtering step considers the current observation z_k and the *a priori* state pdf to generate the *a posteriori* state pdf, by using Bayes Formula [8]:

$$p(x_k \mid z_{1:k}) = \frac{p(z_k \mid x_k) p(x_k \mid z_{1:k-1})}{p(z_k \mid z_{1:k-1})} \tag{4}$$

The actual distributions would then be approximated by a set of samples (5) and the corresponding normalized importance weights $\tilde{w}_k^i = \tilde{w}_k(x_{0:k}^i)$ for the i-th sample [7].

$$p(x_k \mid z_{1:k}) \approx \sum_{i=1}^{N} \tilde{w}_k(x_{0:k}^i) \cdot \delta(x_{0:k} - x_{0:k}^i) \tag{5}$$

where the update for the importance weights is given by:

$$w_k = w_{k-1} \frac{p(z_k \mid x_k) p(x_k \mid x_{k-1})}{q(x_k \mid x_{0:k-1}, z_{1:k})} \tag{6}$$

Fault detection/diagnosis implies the fusion of the inner information present in the feature vector (observations) in order to determine the operational condition (state) of a system. In that sense, a Particle-filter-based Module for fault detection/diagnosis can be implemented by considering the nonlinear state model (7).

$$\begin{cases} x_d(k+1) = x_d(k) + n(k) \\ x_c(k+1) = f_k(x_d(k), x_c(k), w(k)) \\ Features(k) = h_k(x_d(k), x_c(k), v(k)) \end{cases} \tag{7}$$

where f_k and h_k are non-linear mappings, $x_d(k)$ is a collection of Boolean states associated with the presence of a particular operational condition in the system (normal operation, fault type #1, #2, etc.), $x_c(k)$ is a set of continuous-valued states that describe the evolution of the system given certain operational conditions, $n(k)$ is zero-mean i.i.d. white noise and $w(k)$, $v(k)$ are non-Gaussian noise distributions that characterize the process and feature noise pdf, respectively.

The above mentioned implementation allows the algorithm to modify the probability masses associated with each particle, as new feature information is been received. Furthermore, the output of the Fault Detection/Diagnosis Module, defined as the percentage of the particle population that activates each Boolean state, gives a recursively updated estimation for the probability for any given fault condition

Under this approach, long-term predictions are based on the current estimate of the fault dimension and the fault growth model with parameters refined in the posteriori state estimation. A novel recursive integration process based on both Importance Sampling and *pdf* approximation through Kernel functions is then applied to generate state predictions from (k+1) to (k+p).

$$\begin{aligned} p(x_{k+p} \mid z_{1:k}) &= \int p(x_k \mid z_{0:k}) \prod_{j=k+1}^{k+p} p(x_j \mid x_{j-1}) dx_{k:k+p-1} \\ &= \sum_{i=1}^{N} \tilde{w}_k^{(i)} \int \cdots \int p(x_{k+1} \mid x_k^{(i)}) \prod_{j=k+2}^{k+p} p(x_j \mid x_{j-1}) dx_{k+1:k+p-1} \end{aligned} \tag{8}$$

Long-term predictions can be used to estimate the probability of failure in a process, given a hazard zone that is defined by its lower and upper bounds (H_{lb} and H_{up}, respectively). The prognosis confidence interval as well as the expected time-to-failure (TTF) can be deduced from the TTF pdf:

$$p_{TTF}(ttf) = \sum_{i=1}^{N} \Pr\left(Failure \mid X = x_{ttf}^{(i)}, H_{lb}, H_{up}\right) \cdot w_{ttf}^{(i)} \tag{9}$$

B. Implementation of particle filter framework for prognosis of battery grid corrosion

The particle filter technique has been applied to the problem of battery grid corrosion prognostics. The objective is to determine the current level of grid corrosion (diagnostics). Once a problem has been detected, the algorithm determines the probability of the time-to-failure (TTF). The algorithm has been implemented on a computer and tested using simulated data. The computer program generates a number of graphics that update in "real time" to supply the user with up-to-date diagnostic and prognostic information. Samples of these graphical indicators are included in the following paragraphs.

As indicated above, there are two items required by the particle filter procedure. First and foremost, the procedure requires a mathematical model relating the damage evolution of the battery to a particular stress factor. Arrhenius model is widely accepted as such a model for electrochemical system degradation due to temperature as a stress factor [9]. The model is of the form

$$\begin{cases} R(k+1) = R(k) + \alpha(k) \cdot e^{-C_1 / C_2 \cdot T} + v_1(k) \\ \alpha(k+1) = \alpha(k) + v_2(k) \\ T = f(k) \\ Feature(k) = R(k) + n(k) \end{cases} \tag{10}$$

where:
C_1 and C_2 are model constants.
$R(k)$ is the value of the battery internal resistance at time k
$\alpha(k)$ is the estimated value of the unknown model parameter at time k
T is the predicted ambient temperature in degrees Kelvin, specified as a function of k
v_1 and v_2 are Gaussian white noise signals
n is an Uniform white noise signal

The second item required by the particle filter procedure is a set of measurements or observations, so that the filter parameters and the estimate can be updated. The observations are provided here by the "virtual sensor" for the battery internal resistance. This virtual sensor, discussed in Section III, is based on the energy delivered during a brief cranking episode, i.e. $E = \int_0^1 V_{bec} I_{batt}\, dt$. This feature and an estimate of the initial battery SOC under given temperature is used to form an estimate of the internal resistance of the battery, *cf* Fig. 6. Thus, each time that the car is started, an observation is provided to the particle filter.

In the case of battery degradation, it is known that there are a variety of stress factors including temperature, degree of overcharge/undercharge, amount of time that the battery has at low SOC, frequency of engine on/off's per day, etc. In this study, only temperature was considered and an appropriate temperature forecast was used based on data for the past few years, considering that the hypothetical test were to be conducted in Atlanta, GA.

Results obtained under these assumptions have shown that the Arrhenius model can be successfully implemented to solve the prognosis task. In addition, the performance of the proposed Particle Filtering (PF) framework approach has been tested and compared with an Extended Kalman Filtering (EKF) framework for prognosis. Fig. 8a and 8b shows the comparison between the PF approach and the EKF approach in the case of the Arrhenius model of equation (10). It is seen that the precision of the TTF pdf from the PF approach is higher than that of the EKF approach. In particular, the dispersion of the TTF *pdf*'s of the PF approach (magenta in Fig. 8b) is smaller than that of the EKF approach (cyan in Fig. 8b).

Several factors contribute for the dispersion of the TTF *pdf* obtained through the EKF implementation. The most important source of uncertainty for long term predictions using the Arrhenius Model is the assumption of Gaussian white noise for all the states in the model, while the model is considering uniform white noise for the second state. The error in the covariance matrix estimation is successively

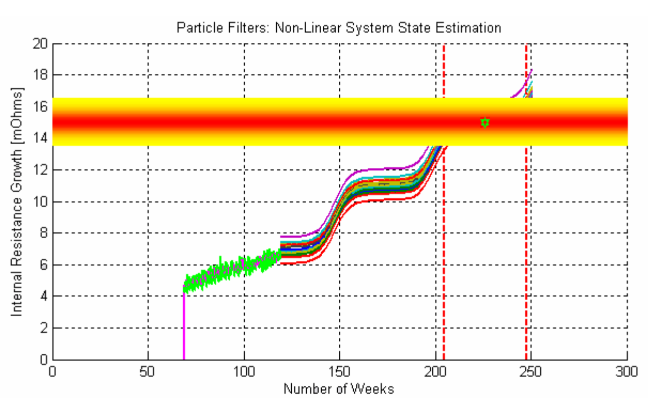

Fig. 8a. Long-term prediction for the internal resistance. The red/orange bar represents the hazard zone.

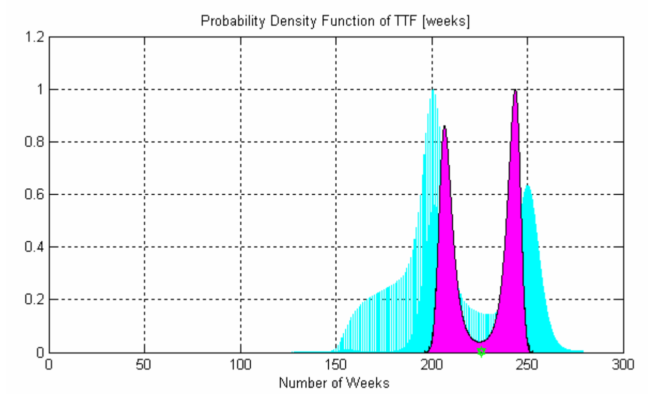

Fig. 8b. Comparison between the TTF pdf estimates obtained respectively from the PF (magenta) and EKF (cyan) prognosis approach.

propagated through future time instants, and again, the absence of feature data in predictions does not allow compensating the estimation error.

V. CONCLUSIONS

This paper discusses a methodology by which diagnosis and prognosis of failure modes in an automotive EPGS system can be accomplished. A specific fault is presented as an example i.e. battery grid corrosion. A feature based on observable signals is developed that is correlated to the underlying fault. The performance is tested through numerical simulations using SABER. Finally, a prognostic algorithm based on particle-filtering is used to determine accurate statistics of the battery's time-to-failure.

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