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ELECTROCHEMICAL CELL DIAGNOSTICS USING ONLINE IMPEDANCE MEASUREMENT, STATE ESTIMATION AND DATA FUSION TECHNIQUES

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ABSTRACT

A method to accurately assess the state-of-charge (SOC), state-of-health (SOH), and state-of-life (SOL) of electrochemical energy sources, such as primary and secondary batteries, can provide significant benefits in operational systems. The model-based effort described here is focused on predictive diagnostics techniques for primary and secondary batteries. This novel approach, however, can also be applied for performance monitoring of other electrochemical energy sources such as fuel cells. This method is based on accurate modeling of the transport mechanisms within the battery and requires careful development of electrochemical and thermal models. These models have been used to develop new features to be used in conjunction with several traditional measured parameters to assess the condition of the battery. Data fusion of feature vectors is used to develop inferences about the state of the system. The resulting output and any usage information available about the battery is then evaluated using hybrid automated reasoning schemes consisting of neural network and decision theoretic methods. The focus of this paper is on model identification and data fusion of the monitored and virtual sensor data. The analysis presented is drawn from the authors experience with electromechanical systems where multiple sensor types are used for diagnostic assessment.

Keywords: Automated reasoning; condition-based maintenance; data fusion; electrochemical impedance; state-of-charge

INTRODUCTION

Batteries are an integral part of many machines and are critical energy backup systems for many power and computer networks. Failure of a battery could lead to loss of operation, reduced capability, and downtime. An efficient way to monitor a battery's performance and assessment of its condition could drastically increase the reliability of these systems. The present condition of a battery is described nominally with it's state-of-charge (SOC), which is defined as the ratio of a battery's remaining capacity to it's initial or rated capacity. This measurement can be reported in two forms, initial SOC before loading or charging, and continuous SOC, which represents the most up-to-date measure of stored energy during discharging/charging. Another indicator of the present condition of a battery is state-of-health (SOH). SOH is a measure of the physical condition of the underlining processes in the battery ranging from external behavior, such as loss of rated capacity, to internal behavior, such as severe corrosion. The remaining life of the battery (i.e. how many cycles remain, usable charge, etc.) is termed the state-of-life (SOL), the prognostic metric. SOL is a measure of the remaining usable energy in a battery and is reported in two classes: Remaining-Useful-Energy (RUE) and Remaining-Useful-Cycles (RUC). RUE refers to the amount of stored energy remaining in a battery assuming a future load profile. This can refer to energy received from recharging or from formation during manufacturing of new batteries. RUC represents the remaining number of times a battery can be recharged before it is considered dead.

In this paper, a model-based effort is presented for predictive diagnostics of primary and secondary batteries. The flow of the model-based predictive diagnostics processing is shown in Figure 1. There are five distinct stages of the processing: 1) measurement of signals relevant to diagnostics; 2) extraction of key features (such as model parameters); 3) charge, health, and life prediction using multiple methods; 4) decision processes that combine the predictions with knowledge and history; and 5) output of predictive information for user display or use by other systems. The specific objectives of the model-based approach described here are determination of the SOC, SOH, and SOL.

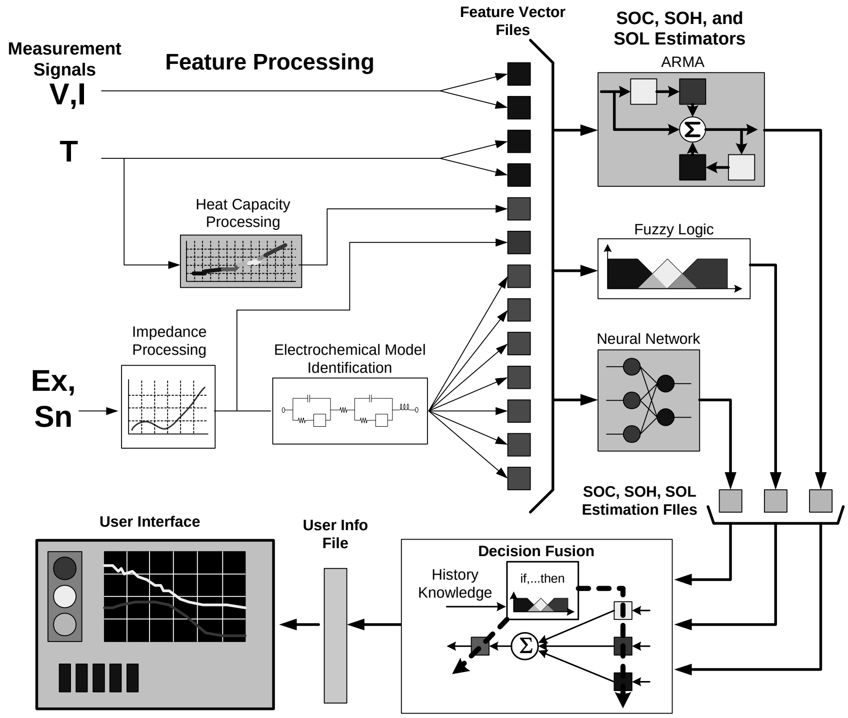

Figure 1. Flow diagram of developed predictive diagnostics processing

Model-based Approach

The general approach to model development is to formulate robustly parameterized governing equations for energy conservation and relevant electrochemical phenomena and transport processes. Lumped parameter formulation in lieu of a spatially distributed formulation offers greater applicability to the broad variety of cell chemistries and battery designs. That is, explicit geometry and configuration input are not required. The parameters and sources of the various transport, state, and conservation equations are coupled to ensure consistency with experimental observations and facilitate system classification. The model parameterization is formulated to incorporate significant aging mechanisms and pathological behavior in order to provide fault diagnostic capability. The ability to forecast future battery performance is developed by tuning system parameters through history-matching trials.

Automated Reasoning and Data Fusion Techniques

A core challenge is to develop the appropriate signal processing, sensor-level data fusion, and automated reasoning to support battery diagnostics, charge control, and ultimately, prognosis of remaining cycles. Multi-sensor data fusion techniques that combine data from actual and virtual sensors provide the potential to improve detection performance and reduce the number of false alarms [1]. The hybrid automated reasoning modules developed previously at the Pennsylvania State University Applied Research Laboratory (ARL) integrate a variety of predictive diagnostic techniques, such as neural networks, fuzzy logic, and auto-regressive moving average (ARMA) models, via decision-level data fusion [2, 3]. The outputs of these techniques are three estimates of the battery condition based on electrochemical and thermal data and available usage information. They are combined using hybrid automated reasoning modules, consisting of neural network and decision theoretic methods, to provide a single estimate of the battery's state. This output can be obtained as a linguistic indication or as numerical indication and is coupled with a measure of confidence.

MEASUREMENT AND DATA COLLECTION

The first step to developing model-based diagnostics is to establish the necessary and available observables (i.e., what can be measured and its sufficiency). Changes in the electrode surface, diffusion layer, and solution are not directly observable without disassembling the battery cell. Other variables, such as potential, current, and temperature, are observable and can be used to indirectly determine the performance of physical processes. This is the rationale for choosing a model-based approach. Under these constraints, the following types of measurements were selected for battery diagnostics: terminal and cell voltages, load currents, surface and internal temperatures, electrolyte pH, and electrical impedances. To ensure maximum coverage of operating modes for testing developed algorithms, test stand data were collected under the following conditions: no load-fully charged, once every minute during discharging, no load-fully discharged, and once every minute during charging. An ongoing experimental test schedule is being conducted in which lead-acid, nickel-cadmium, lithium, and alkaline batteries are cycled until failure. During a test, battery impedance data is collected along with cell and terminal voltages, load current, and temperatures at various internal and external locations on the battery. To date, over 200 data sets have been collected across the different chemistries and sizes of batteries.

ELECTROCHEMICAL IMPEDANCE MODEL IDENTIFICATION

Direct measurements of battery or cell condition have traditionally been very difficult for practical systems such as automotive or aviation batteries. There are, however, a variety of indirect measurement techniques that rely on the cell's response to a precise manipulation of the load [5, 6, 7]. One of the most robust and widely used methods in laboratory practice is AC Voltammetry. This technique can provide information on the electrochemical dynamics of the battery through a non-invasive interrogation of the cell. By applying a small amplitude excitation to the cell and measuring the response, the internal impedance of the cell can be determined. A patent pending impedance technique (US application # 09747,341; PCT application # PCT/US00/35044) has been developed at ARL for more accurate measurement. This device also makes online measurement possible so that the dynamic performance of the battery can be estimated. In addition, unlike most AC Voltammetry techniques, a range of frequencies is used for excitation of the cell. This accounts for the frequency dependency of many of the electrochemical impedance parameters being measured.

Internal impedance measurements can further be used to retrieve information about the electrochemical processes that occur within the battery. This is accomplished using electrical circuit analogs such as the Randles circuit, which represents the electrode, the electrolyte interface, and transport processes. A better fit of the impedance data was demonstrated in our current work using a two-electrode Randles circuit model along with a global search routine for optimization of parameter (virtual sensor) identification (Figure 2).

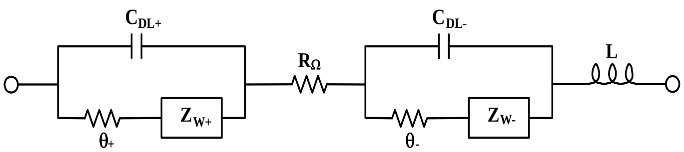

Figure 2. Two-electrode Randles circuit model with wiring inductance

The equation for this circuit is given as

$$Z_{cell}(s) = \frac{s^{1/2}\theta_+ + \sigma_+\sqrt{2}}{s^{3/2}\theta_+ C_{DL+} + sC_{DL+}\sigma_+\sqrt{2} + s^{1/2}} + R_\Omega + \frac{s^{1/2}\theta_- + \sigma_-\sqrt{2}}{s^{3/2}\theta_- C_{DL-} + sC_{DL-}\sigma_-\sqrt{2} + s^{1/2}} + sL \quad (1)$$

In (1), s = jω (ω is frequency in rad/s), R_Ω represents the electrolyte resistance, θ represents the charge transfer resistance, C_{DL} represents the double layer capacitance, σ represents the diffusion layer coefficient, and Z_{cell} represents the Warburg impedance (Z_W) of the cell. These parameters represent the physical electrochemical processes, such as charge and mass transfer, which occur during cycling. See [5, 6, and 8] for a description of these electrochemical processes.

The above parameters are extracted from the impedance measurements using a minimum search routine. For this approach, a simulated annealing algorithm was chosen. Unlike many local minima search methods, simulated annealing offers a global search [9-12]. Search regions, based on the identified parameters from previous impedance measurements, are used to minimize processing iterations. The model-identified electrolyte resistance of a nickel-cadmium battery during discharge, which was found using simulated annealing, is shown in Figure 3.

STATE-OF-CHARGE PREDICTION MODELS

The previous section addressed the extraction of physically meaningful parameters, such as charge transfer resistance, to more strongly connect SOC, SOH, and SOL predictions to internal battery processes. These *virtual sensor* signals (i.e., identified model parameters) also provide the decision processing with a check for bad signals. Referring to Figure 1, this section focuses on the developed SOC prediction modeling, including models for both initial and continuous SOC predictions.

In order to evaluate the SOC of a cell, two types of models have been developed, one for initial SOC (ISOC) prediction, and another for continuous SOC (CSOC) prediction. ISOC predictions produce a continually updated estimate of the amount of initial charge present in the battery prior to its discharge. This provides more reliable information than

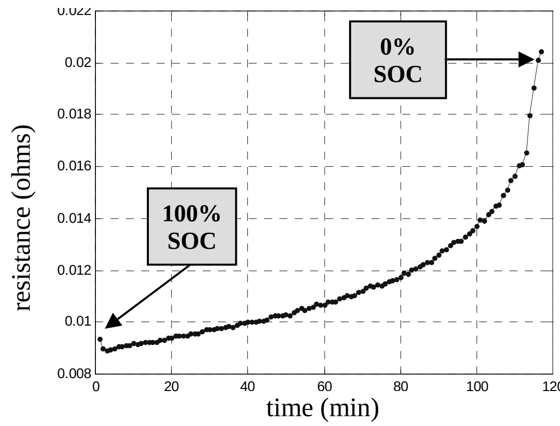

Figure 3. Model-identified electrolyte resistance of a nickel-cadmium battery using simulated annealing

the rated capacity, which varies with temperature and loading. In order to account for changes in these parameters, ISOC is continuously updated during the cycle. The second model type, for CSOC prediction, provides the most up-to-date measure of stored energy during a battery cycle. It is updated using the electrochemical characteristics of the cell and changing ISOC predictions.

ARMA Modeling

Autoregressive (AR) modeling is a powerful linear modeling technique employed for predictive diagnostics [3]. In order to assess battery capacity, an analytical model of battery dynamics is useful. Autoregressive moving average (ARMA) modeling is commonly used for system identification because it is linear and easy to implement. It is also a good complement to the more complex models (neural network and fuzzy logic) being used. Two ARMA models were chosen for assessment of battery SOC (one each for ISOC and CSOC), and are both represented by the equation:

$$y(t)=a\,X(t) + b\,X(t-1) + c_o\,y(t-1), \quad (2)$$

where y represents SOC, X represents a vector of model inputs, and a, b, and c_o represent the model coefficients. Model coefficients are calculated during training of the model, where a least squares fit of data from a previously discharged battery is performed [13]. The model uses instantaneous measurements, as well as past measurements of the system, to monitor changes in the system. Inputs to the models include: electrochemical impedance parameters, voltage, current and temperature measurements, and past SOC predictions. CSOC model inputs are preconditioned using a low-pass filter, gradient analysis, and parameter normalization. Preconditioning of ISOC model inputs is not performed.

The ARMA models have been trained and tested on five different kinds of batteries with varying size, chemistry, and type: two sizes of primary poly-carbonmonofluoride $(CF)_x$ lithium (C and 2/3 A), two sizes of secondary nickel-cadmium (C and D), and one size of secondary lead-acid (12 volt). Results from both the CSOC and ISOC ARMA models can be found in Table I. Model refinement (input selection and preconditioning) was chosen based on model performance for size C lithium batteries and performance is very impressive (1 to 5 % error). The same models were also trained for the other types of batteries (size and chemistry), but model refinement has not yet been completed. Despite this lack of model refinement, the models performed very well on these batteries. This is quite impressive and reflects the robustness of the ARMA models if trained on a battery of the same type. These results are expected to improve once model refinement is performed for these types as well.

Table I. SOC Prediction Results for ARMA, Neural Networks, and Fuzzy Logic models

Chemistry	Size	# Cells	Type	ARMA		Fuzzy Logic		Neural Networks		Hybrid	
				CSOC Error (%)	ISOC Error (%)	CSOC Error (%)	ISOC Error (%)	CSOC Error (%)	ISOC Error (%)	CSOC Error (%)	ISOC Error (%)
Lithium[1]	C	1	Primary	**1.41**	**3.54**	**1.25**		**2.7**	**2.1**	1.79	2.82
Lithium[1]	2/3 A	1	Primary	1.42	6.69	6.85		**4.7**	**3.4**	4.32	5.13
Ni-Cad[2]	C	1	Secondary	1.09	5.51	1.38			3.3	1.24	4.41
Ni-Cad[2]	D	1	Secondary	2.36	5.07	1.84			3.8	2.10	4.44
Lead-Acid	12 Volt	6	Secondary	9.13						9.13	

[1] Poly-carbonmonofluoride-lithium (spiral type) [2] Nickel-cadmium

Neural Network Modeling

An *artificial neural network* is a parallel distributed processing system inspired by biological neural networks. It consists of information processing units, called *neurons* or units, that are interconnected through *connection weights* to produce a desired output in response to its inputs. Similar to the ARMA models, networks were trained to produce both ISOC and CSOC predictions. All networks used for battery SOC estimation contained one hidden layer of neurons. The back propagation gradient-descent learning algorithm was used, which utilizes the error signal to optimize the weights and biases of both network layers. The performance of the neural networks for CSOC prediction was found to be quite consistent. The results for size C lithium batteries (runs 9-16) and size 2/3 A lithium batteries (runs 17-25) are given in Table I.

Networks were also trained to estimate the initial capacity of the battery (ISOC) during the first few minutes of the test. The SOC of the battery was then calculated directly by using the cumulative discharge current. This method can be a powerful tool for *mission planning*. Hypothetical load profiles could be used to predict whether the battery would survive or fail during a given mission, thus preventing the high cost and risk of batteries failing in the field. Results of this network on lithium and nickel cadmium batteries are also given in Table I.

The SOC assessment by neural networks was very good. Although the average error is slightly higher than for the ARMA predictors, two important strengths of the neural network predictors outweigh that drawback: (i) maximum error on outliers was not significantly larger than the average error, and (ii) the network provides a conservative prediction (i.e., it does not over-predict the SOC). Both of these advantages are very important in practical systems where certification and low false alarms can impact whether a system is actually used or shelved.

Fuzzy Logic Modeling

Fuzzy Logic provides a non-linear mapping of an input data vector to a scalar output by combining numerical data with linguistic knowledge [14]. The advantage of using fuzzy logic is that it extends Boolean logic to account for the concept of partial truth, that is, the area between absolute truth and absolute false. Fuzzy logic algorithms classify model inputs using *membership functions,* which output a numerical value between 0 and 1 indicating how well the input fits into the particular class. A knowledge based rule set is then implemented to map the inputs to the desired output.

For this effort, a CSOC prediction model has been developed and tested on lithium and nickel-cadmium batteries. An important development in the refinement of this model is the use of a regressive variable representing the previous fuzzy CSOC prediction. Much like the ARMA model, this variable gives the model knowledge about the history of the battery cycle. This benefits the performance of the model by narrowing the window of possible predictions. Model inputs are preconditioned using a low-pass filter and a gradient analysis. Results are similar to the ARMA and neural networks models and can be found in Table I. Efforts are currently under way to develop a fuzzy logic model for ISOC prediction. These models, however, are still in the developmental stage and results are not presented here.

SOC Modeling Remarks

Considering limited training data are used to produce the predictions, results for all three models are quite impressive. As more data are collected and several runs of each level of initial battery SOC become available, the robustness of the predictors is likely to improve. The key distinction between the three approaches used is that the ARMA model assumes an explicit linear form of the predictor, while the neural networks and fuzzy logic models attempt to discover an implicit nonlinear model that captures the intricacies of the battery dynamics. If the model is of adequate degree, the ARMA model should require fewer runs than the other two. However, the neural network and fuzzy logic models can better represent nonlinearity and, thus, provide better generalization across the sample. Results are also impressive when compared to other published results of SOC prediction. *The results presented here (1-5% error) reflect an order of magnitude improvement over other published techniques (10-15% error)* [7]. Error results presented in Table I represent the mean error of the predictions throughout the entire discharge of the battery.

FAULT AND END-OF-LIFE PREDICTION

For primary batteries, the SOC is also the SOL; once the charge is depleted the battery cannot be used again. However for secondary batteries, the SOC only represents the cycle life and not the total life of the battery because multiple discharges are possible.

State-of-Health

For secondary batteries, the life of the battery is defined by the number of usable cycles that remain until failure. For example, batteries are commonly removed from service when their discharge capacity has been reduced to 65% of the original capacity, indicating the end limit for usable cycles [14]. Other end-of-life conditions include short-circuited cells and low terminal voltage. In addition, a number of aging mechanisms (dry-out, passivation, etc.) progress during a battery's life, resulting in its eventual failure. Each mechanism wears the battery at a different rate and simultaneous failure progression is common. Identifying which faults are occurring and to what degree will dictate the SOL prediction model that should be used. This classification of faults is an estimation of the battery's SOH.

Much like the SOC approach to having three separate, parallel processing methodologies for prediction, the SOH estimation processing involves three different processing branches: statistical pattern recognition using linear discriminant functions, neural network-based pattern recognition, and fuzzy logic-based classification [14,15]. Figure 4 demonstrates an example of battery failure identification using statistical pattern recognition. Axis labels α and β represent measured or derived parameters that are used to identify the failures in feature space.

Much like SOC prediction, SOH classification will benefit from the use of decision fusion. Domain knowledge and test data can be used in combination to take advantage of the complimentary benefits of implicit and explicit knowledge representations, while avoiding their disadvantages [2]. At this time, limited data on the different failure modes is available. Since the failures are not seeded, batteries are transitioned to failures under controlled operating conditions only. Depending on chemistry and design, data collection must endure tens to thousands of charge/discharge cycles to acquire a complete set of battery failure data. Therefore, much of this work is in early stages; results and further detail will not be provided here.

State-of-Life

Once faults and their severity are identified from the SOH processing, the proper SOL prediction model can be selected. Figure 5 shows a case where dry-out was identified as the dominant SOH condition. As a result, a dry-out trained SOL predictor was used to predict the number of Remaining-Useful -Cycles (RUC). Had a different dominant failure mechanism been identified from the SOH processing, a different RUC-SOL prediction model would have been used. Remaining-Useful-Energy (RUE) SOL predictions are also possible using ISOC and CSOC predictions and a desired load and temperature profile. These predictions indicate how much longer a battery can be used for the conditions given. This is a valuable parameter for *mission planning* and other decision-making operations.

DECISION FUSION PROCESSING

As previously mentioned, the SOC, SOH, and SOL processing are each performed in three parallel streams. This approach provides three assessments of the battery's condition. These three predictions are fed into a decision-processing module that determines the predictors' effectiveness relative to each other, processed sensor data, previous history, and knowledge about the battery type. The decision processing uses this information, via hybrid automated reasoning modules, to yield a combined prediction of the SOC, SOH, or SOL with a measure of confidence. Several decision-level fusion techniques exist including Voting, Weighted Decision, and Bayesian Inference. Other techniques, such as Dempster-Shafer's method and Generalized Evidential Processing theory, are also

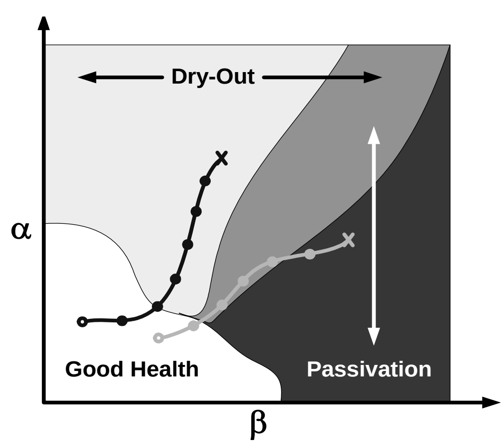

Figure 4. Failure identification using statistical pattern recognition in a lead-acid starter battery.

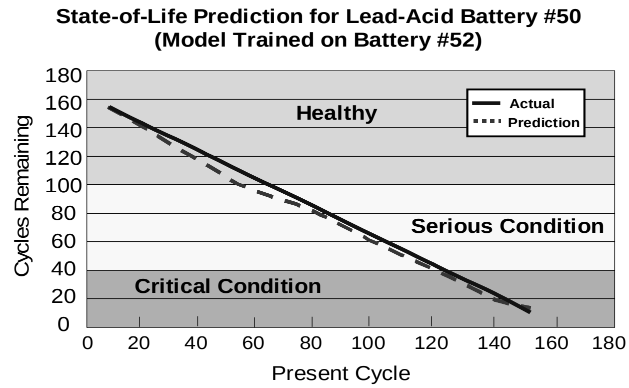

Figure 5. ARMA SOL prediction based on dry-out dominated SOH

available[1- 3]. Table II depicts an example of data fusion for the three SOC predictors using the weighted decision technique. Each prediction is assigned a weight based on predictor agreement, previous model performance, and knowledge about the battery type. Referring to Figure 1, decision fusion represents the final stage of the processing; the output is then fed to a user interface that can display or coordinate the battery condition data.

ERROR ESTIMATION

Whenever an estimate or prediction is computed, it is important to also estimate the expected error in the estimate or prediction. This is essential for establishing and improving the reliability of battery management in operational systems. Statistical approaches for error estimation and minimization may not be feasible since operational data is expected to be sparse, at least in the near future. Furthermore, the number of variables that can influence the SOC is quite large and even if a systematic data collection program were established, it would take significant time and money to collect sufficient data. The model-based effort described here is helpful in reducing the number of random variables significantly. Since voltage, current, temperature, and internal electrical impedance of the battery are closely related to battery SOC and aging, these and certain derived parameters can be used to assess the expected error. Unfortunately, estimation error is not treated adequately in most applications. In this discussion, estimation and prediction errors are both termed as estimation error since they can be treated the same during the characterization process. Estimation error is a broader term and, in fact, prediction error can be seen to be a special case of estimation error.

The goal of error characterization is to assess the a posteriori estimation error and, if possible, to reduce it. While it is actually possible to reduce the impact of most of these errors, estimation error is typically not computed or is ignored. Consequently, the errors can compound and statistical estimates of estimation error grossly underestimate the true error. The impact of this is most clearly seen in the poor performance of usual prediction techniques in real-world situations. A comprehensive approach for error characterization for battery SOC prediction is being undertaken so that decisions made based on SOC estimates are more reliable. In particular, this approach addresses the complimentary objectives of improved accuracy and improved confidence. The overall estimation error is a function of many factors, including: errors in measurement, errors in modeling, improper propagation of errors through the estimation process, inherent variability in components, variability in the actual use of batteries due to differences in user's individual style and mission, incorrect knowledge of a priori conditions, exclusion of variables that impact SOC (i.e. temperature), lack of a physical link between the estimation parameters and physical processes, treatment of sources of error as completely independent of each other, non-inclusion of failure mode information in SOC estimation and error estimation, and inadequate use of

Table II. Example of SOC data fusion (weighted decision)

SOC (%)	ARMA % SOC (WEIGHT)	NEURAL NET % SOC (WEIGHT)	FUZZY % SOC (WEIGTH)	HYBRID % SOC (% ERROR)
10.1	11.9 (0.4)	10.3 (0.4)	13.3 (0.2)	11.5 (1.4)
9.8	11.6 (0.3)	9.8 (0.5)	13.0 (0.2)	11.0 (1.2)
9.5	11.3 (0.4)	8.9 (0.4)	12.7 (0.2)	10.7 (1.2)
9.3	11.1 (0.4)	8.1 (0.3)	12.4 (0.3)	10.6 (1.3)
9.0	10.8 (0.4)	7.9 (0.3)	12.2 (0.3)	10.3 (1.3)

data fusion to reduce error and uncertainty. Presently, several methods for including these factors are being pursued, including formulation of error in modeling, statistical estimation of error, use of data fusion to reduce error via corroboration (or rejection) of estimates, incorporation of failure mode information when it is available, etc.

Another important aspect of error estimation is that it should be possible to determine the error as a function of time. In other words, it should be feasible to determine when in time the greatest estimation error is occurring. The most significant benefit of this is that estimation accuracy is known at the time of decision. This is contrast with the typical approach where average estimation error is reported and it is unclear whether the largest error occurs when the SOC is large or small. Reporting the error as a function of time allows identification of intervals of time during which the error is large. It is then possible for the user to determine whether the larger error is a problem based on the operational profile of the battery. For example, larger estimation error which occurs during the transient phase of the battery, e.g., start-up or during load changes, is not of as much concern as that which occurs during steady state phase of the battery. Assessment of error in the estimation process is essential for establishing the validity of the estimator and for providing a sound basis enhancing its reliability. Furthermore, it can also show which portion of the overall process is contributing the most to the overall error. This assessment can be used to take steps to reduce that source of error.

SUMMARY

Condition-based maintenance provides a means for improving the reliability of battery management in operational systems. For primary batteries, this represents providing the user with a SOC estimate to allow him/her to decide when to replace it. This capability has some obvious benefits in critical military applications for instance. For secondary batteries, this represents basing maintenance and replacement decisions upon estimated conditions and the predicted remaining cycles available to the user. In the case of a backup or standby battery, this represents knowledge of usage capacity prior to putting the battery online.

The model-based approach described in this paper provides a framework for robustly predicting SOC, SOH, and SOL. It has been shown that in addition to voltage, current and temperature, the internal electrical impedance of the battery ties closely to the physical processes that drive capacity and aging. ARL's patent pending impedance technique used in this work provides a more precise measurement that is less susceptible to noise. This device also makes online measurement (while the battery is being cycled) possible so that the dynamic performance of the battery can be estimated. In addition, unlike most AC Voltammetry techniques, a range of frequencies is used for excitation of the cell. This accounts for the frequency dependency of many of the electrochemical impedance parameters being measured. The identified parameters are not tied to a specific frequency, but rather they represent the virtual sensors in a modified Randle's circuit model. The use of simulated annealing as a search routine also provides a more accurate identification of model parameters because it provides a global search, rather than a local search (i.e. least squares) like many SOC predictors use. The developed ARMA, neural network, and fuzzy logic SOC prediction models were discussed and shown to perform well across different battery chemistries and sizes. Some initial results were presented from the SOH and SOL prediction development; however, this work is still in its early stages. The framework for the decision fusion processing, which provides additional error checking and performance enhancement, was also discussed. Lastly, the concept of using the SOH classification to aide in SOL prediction to produce more accurate end of life predictions was suggested and error estimation procedures were discussed. Most of the analyzed data for this effort was collected on a laboratory test stand under controlled environmental and load conditions. Plans are being made to collect field data to test the developed model-based predictive diagnostics on battery systems (and other electrochemical energy sources) under real-world operating conditions.

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