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Use of Model-Based Design Methods for Enhancing Reliability of Self-Adaptive Systems

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Abstract

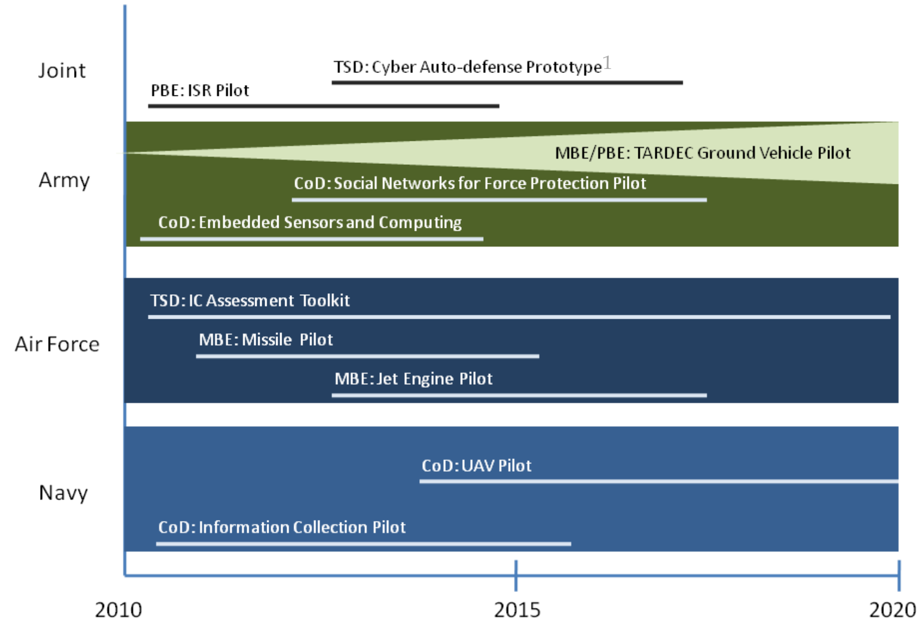
Over the last decade, the need for more complex military defense systems has become increasingly apparent. As new threats continue to evolve and advance quickly, so does the need for on demand capability to defend against them. Self-adaptive systems allow the military to quickly react and adapt to changing threat environments intelligently with minimal human interaction and degradation of mission performance. This growing area has experts concerned about maintaining a high level of system reliability. It's become increasingly difficult to apply traditional methods of reliability analysis to design proposed future defense systems. Although designing for reliability is a proven challenge, with the proper design framework in place, one can enhance the reliability of self-adaptive systems through use of model-based design methods. In this briefing, a preliminary model-based design approach is proposed that allows for an integrated qualitative and quantitative analysis for enhancing the overall reliability of systems with self-adaptive capability. A case study with applicability to military defense will be used to prove out initial model-based concept.

Systems 2020

According to the Department of Defense (DoD) Systems 2020 report, future systems will become increasingly complex.

Self-adaptive capability on demand (COD) allows systems in the field "to rapidly respond to a changing environment as the mission evolves in unplanned, unforeseen ways" (Boehm).[1]

This growing area has experts concerned about the reliability of these evolving systems.



There will be a need for faster, more flexible, and more adaptable systems.[1]

[2]

It's become increasingly hard to apply traditional methods of reliability analysis to design proposed future systems.[1]

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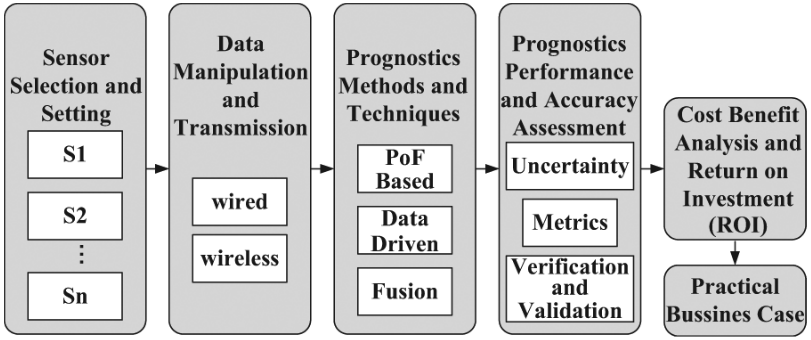
Enhancing Reliability of Self-Adaptive COD Systems

In Self-Adaptive COD Systems, there is great opportunity to enhance reliability in the area of composable DoD components.[1]



Major components of prognostics implementation[3]

For example, embedded sensors and computing components can be composed to generate, filter, and analyze data.[1]

Model-Based Prognostic Health Management can be applied though use of algorithms to measure, monitor, and predict system performance.[3]

With the proper design framework in place one can enhance the reliability of self-adaptive systems through use of model-based design methods.

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Model-Based Prognostics

Benefits of PHM [3]

Allows for quantitative analysis

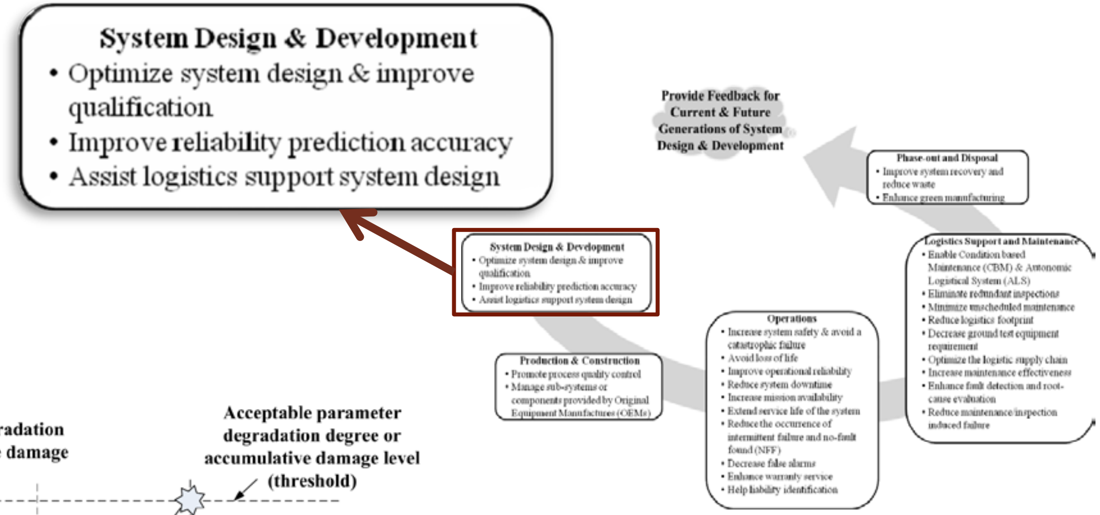
Permits the reliability of a system to be evaluated in its actual life cycle conditions.

Improves system safety

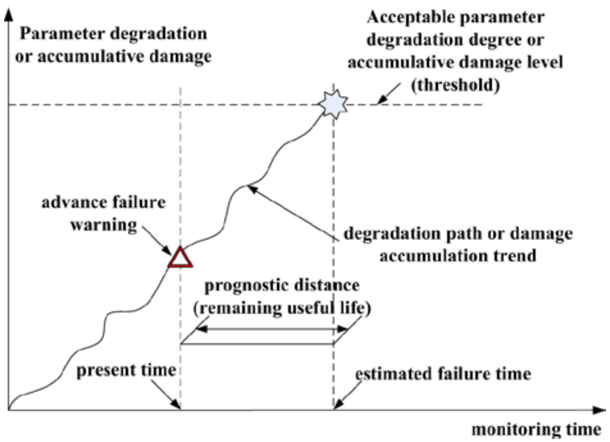
Increases system operations, reliability, and mission availability

Decreased unnecessary maintenance actions

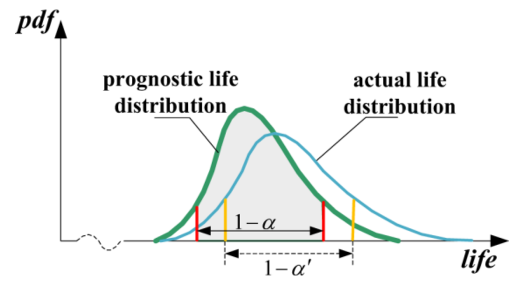
Reduced system life-cycle costs (LCC)



Potential benefits of prognostics in system life cycle process [3]



Advance failure warning capability of prognostics [3]



Schematic illustration of prognostic accuracy concept [3]

For military applications, the U.S. Army includes prognostics technology in their weapons platforms and support vehicles. PHM implementation is explicitly stated in the DoD 5000.02 defense acquisition policy document .[3]

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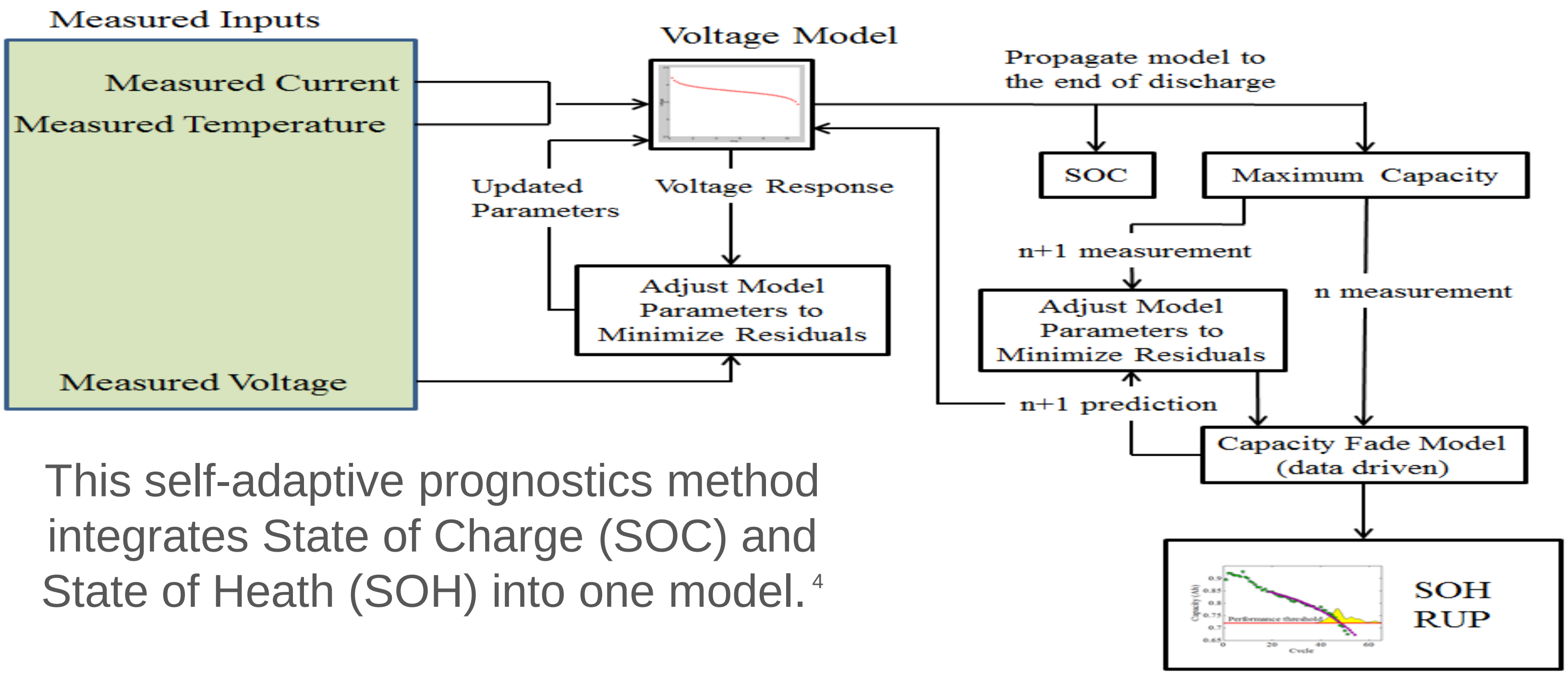
Case Study: Self-Adaptive Battery Management System



This self-adaptive prognostics method integrates State of Charge (SOC) and State of Heath (SOH) into one model. [4]

Generalized Process Flow for Battery State Estimation[4]

This Self-Adaptive BMS uses SOH predictions to update the SOC estimator in order to minimize drift due to capacity loss and cell degradation.[4]

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Data

CS2 Lithium-ion Battery[4,5]

- Commercial single cell battery
- Rated Capacity: 1.1Ah
- Weight: 21.1g
- Dimensions: 5.4 X 33.6 X 50.6 mm
- Composed of standard materials typical of batteries for in portable devices
  - Cathode with $LiCoO_2$ particles adhered to an aluminum current collector with a polymer binder
  - Anode with graphite particles deposited on a copper current collector.
  - Electrodes separated by a polymer matrix and cell doused in LiPF6 solution and organic solvents to provide electrolyte.

Generalized Process Flow for Battery State Estimation[5]

Arbin BT2000 Battery Test System[5]

Test Conditions[4]

- Equipment
  - Arbin BT2000 Battery Test System
- Performed life cycle testing
  - Constant current/constant voltage protocol used.
    - Applied constant current of 0.55A to charge until terminal voltage reached 4.2V.
    - Applied constant current of 0.55A to discharge until cut-off voltage threshold of 2.7V was reached.
  - Time data was sampled every 30 secs.
  - Sampled data at room temperature.

Using the Arbin BT2000 Battery Test System a single cell Lithium-ion battery was tested using a constant current/constant voltage protocol.[4]

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Approach

- The equivalent circuit model (ECM) was derived to model the voltage of battery. It's parameters were pulled from the battery's impedance spectroscopy Nyquist plot data.[4]
- From the model, a time and current dependent equation for the terminal voltage under constant discharge was developed.[4]

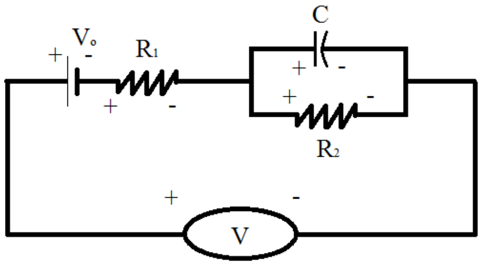
$$V\ \ t; I\ constant\ = \frac{Q(0)}{C}\, e^{-t/(R_2 C)} + V_o - IR_1 - IR_2\left[1 - e^{-\frac{t}{R_2 C}}\right]$$

where, R_1 and R_2 are restrictive components and C are capacitive components extracted from the plot, Q(0) is initial capacity (below), I is current, t is time, V_0 is the open circuit voltage (OCV). V_0 is saved in a look up table.

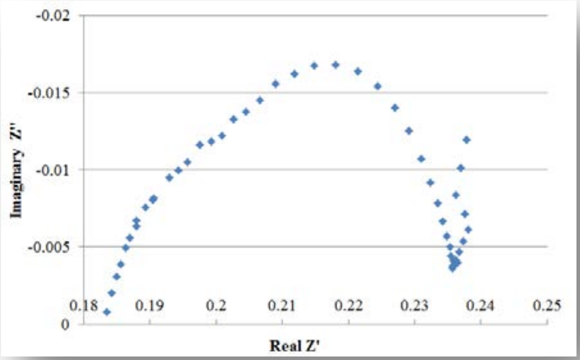
$$Q\ \ 0\ = {}_{t_1}^{t_2} Idt$$

To find initial Q(0) and V_0 a preliminary charge/discharge cycle is conducted at 0.55A.[4]

where, t_1 is fully charged time and t_2 fully discharge time.



Schematic of Equivalent Circuit[4]



Nyquist Plot[4]

Component	Value
R_1	0.18Ω
R_2	0.06 Ω
C	30F

Extracted ECM values[4]

The Voltage Model shows the relationship between SOC and the terminal voltage of the battery under constant discharge.[4]

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Approach cont.

- OCV is calculated by averaging the terminal voltages of the first charge with the voltages of the first discharge cycle. [4]
- The values of R_1, $Q(0)$, and V_0 are continuously updated in the voltage model using n+1th cycle capacity predictions. [4]
- The capacity predictions are calculated with a capacity fade model [4]

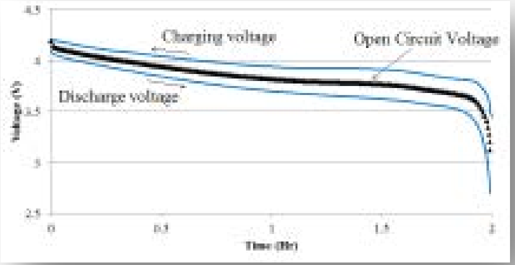
$$Q = a \cdot \exp(b \cdot n) + c \cdot \exp(d \cdot n)$$

Unscented Kalman Filter technique is applied at the end of each discharge cycle to predict the n+1 capacity. [4]

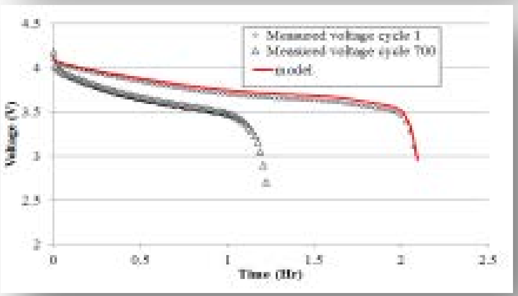
where Q is the capacity, *n* is the cycle number, and *a* through *d* are the model parameters updated at the end of each discharge.

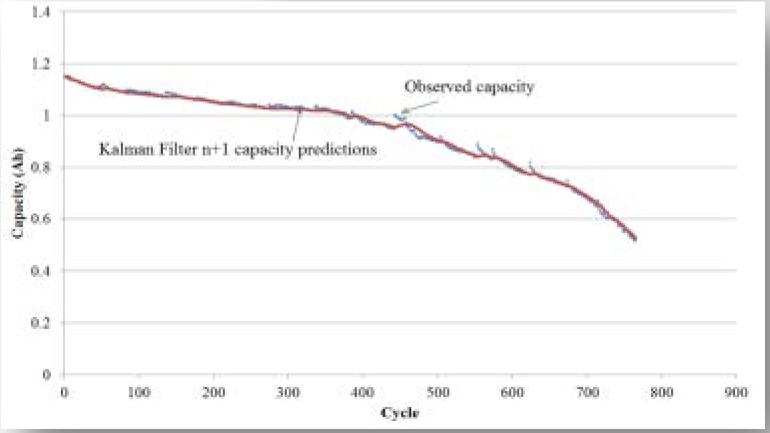
These updates allow the model to best reflect the measured capacity.

Calculation of OCV [4]



Initial Equivalent Circuit Model vs. Measured Discharge Voltage at Cycle 1 and 700 [4]





Results of UKF on Capacity Fade Data [4]

The Capacity Fade Model can determine the SOH through evaluation of the amount of capacity degradation that has occurred in the battery.[4]

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Approach cont.

- The time in the OCV look up table is calculated by dividing the capacity by the discharge current for k number of cycles. [4]

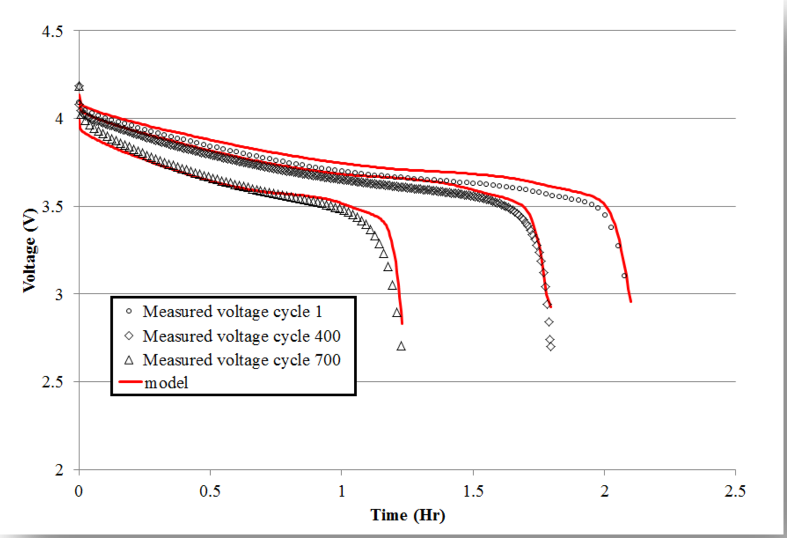
$$T = [1 \cdot \frac{Q}{i \cdot k}, 2 \cdot \frac{Q}{i \cdot k}, 3 \cdot \frac{Q}{i \cdot k}, \ldots, k \cdot \frac{Q}{i \cdot k}]$$

where, Q/i is the time to the end of discharge.

- Non-linear least squares regression was used to find the updated value of R_1 at the end of each discharge. [4]

$$R_1 = -0.5349 \cdot Q + 0.7684$$

This minimizes residuals between the voltage equation and measured voltage values



Measured Voltage Curve vs. Model at Cycles 1, 400, and 700 [4]

SOH degradation can be projected into the future to estimate the battery's remaining useful performance (RUP). RUP predictions are useful to create a reliable condition based maintenance strategy for battery replacements. [4]

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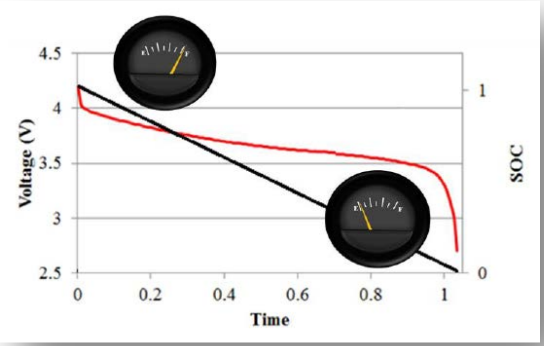
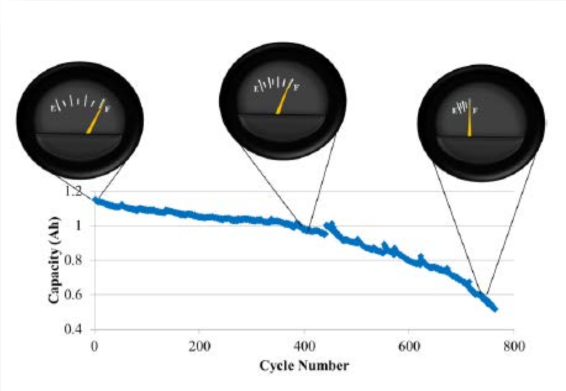
Results

- Although the Self-Adaptive BMS over predicts the voltage in first cycle, it is able to adapt as the battery ages. [4]
- With this model you can estimate the SOC and SOH in the same model to produce a self-adaptive capability. [4]
- The model is a generalized framework that allows for different combinations of voltage and capacity fade models to work together. [4]
- Results of SOC and SOH can be displayed on a fuel gauge that is easily interpreted by users of fielded systems. [4]



Discharge Voltage (red) and the Corresponding SOC Gauge Mapping (black) [4]



Reduction of Available Charge as Capacity Decreases Over Each Cycle Use [4]

A model-based design method successfully modeled a self-adaptive BMS at constant current/constant voltage. Can we achieve similar level of reliability of prediction using data with dynamic characteristics?

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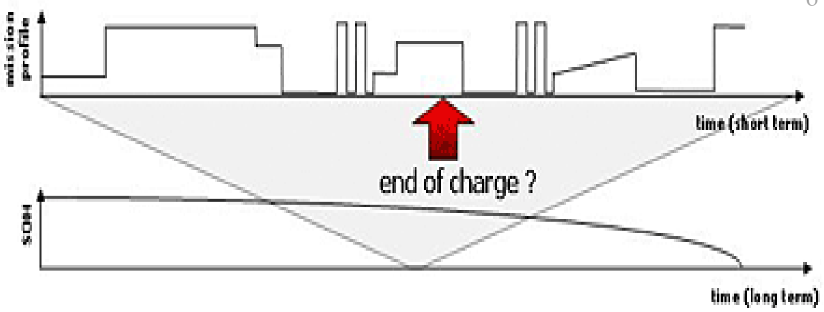
Considerations under Dynamic Conditions

- Battery degradation can vary based on
  - relationships between the usage load profile of the application and environmental conditions.[4]
  - variations in materials and particle contaminates in the battery used.[4]

- Multi-cell battery pack can be subject to overcharging, overheating, and/or short circuit issues [4]

[6]



For example, a UAV should consider the following conditions:[6]

- Mission travel distances
- Ambient storage temperatures
  - Increased temperature increases discharge rate/causes drop in voltage.
- Takeoff/landing and cruise power requirements

Battery degradation under dynamic conditions are highly dependent on parameters such as temperature and power requirements. [5]

Self-Adaptive BMS Algorithms Under Consideration

According to NASA, the following battery prognostic algorithms are under consideration in the industry:

Autoregressive Integrated Moving Average (ARIMA) [6]

- data-driven approach
- linear model
- used for baseline comparison with other approaches

Extended Kalman Filter (EKF) [6]

- classical approach to non-linear state estimation
- use of model
- relatively fast execution time (although slower than data-driven techniques)

Relevance Vector Machine (RVM) [6]

- state of the art in nonlinear probabilistic regression
- very fast

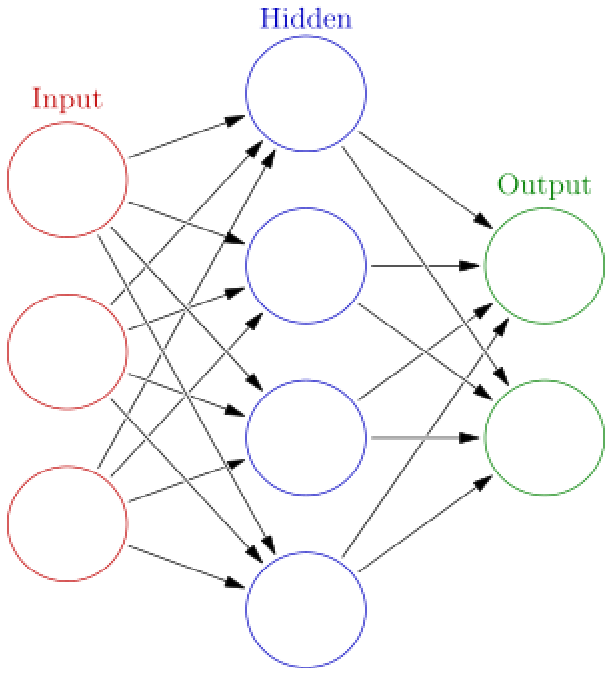
Particle Filter (PF) [6]

- state of the art for nonlinear non-Gaussian state estimation
- slower than Kalman Filter
- uses model

NASA is currently considering a combination of prognostic algorithms to best estimate SOC, SOH, and RUP of Lithium-ion batteries. [6]

Proposed Approach to Dynamic Self-Adaptive BMS

- Test and verify the Capacity Fade Model in a dynamic environment using a supervised machine learning technique. (e.g., Artificial Neural Networks)
- Using collected data, the machine learning algorithm utilizes pattern recognition and regression to find a function that better maps a set of inputs to it's known correct output.[7]
- Parameters inputs can include parameters such as current, voltage, temperature, internal resistance, and number of cycles.



Artificial neural network nodes [7]

The use of machine learning neural networks can enhance reliability of battery degradation predictions in self-adaptive BMS.[7]

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Summary

- A Self-Adaptive BMS uses the concepts of Model-Based PHM to accurately predict remaining useful performance of a Lithium-ion battery.
  - A generalized model has been verified using a constant current/constant voltage protocol.
- In order to enhance the reliability of this self-adaptive system under dynamic conditions, a supervised machine learning technique approach was proposed.
- Future work will include testing data with dynamic characteristics under this new proposed approach.

For more information, please contact Lenora Knox at lenora.a.knox@gmail.com

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Lenora Knox earned a B.S. in Industrial Engineering from Morgan State University and a M.S. in Engineering Management from University of Maryland, Baltimore County. She has 6 ½ years of professional engineering experience in the defense industry and is employed as a Systems Engineer at Northrop Grumman Electronic Systems. Her professional experience areas include Intelligence, Surveillance and Reconnaissance (ISR), Electronic Warfare (EW), and Advanced Concepts & Technology Development (AC&TD). In 2013, she was honored at the 27th Annual Black Engineer of the Year Award (BEYA) conference as a recipient of the Modern-Day Technology Leader Award. Lenora is currently a Ph.D. candidate in Systems Engineering at The George Washington University.