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A self-cognizant dynamic system approach for prognostics and health management

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HIGHLIGHTS

- Developed a self-cognizant dynamic system approach for battery health management.
- Can adaptively recognize battery system models over time considering degradation.
- Employed a feed-forward neural network (FFNN) as the intelligence unit.
- Integrated the FFNN with the Kalman filters to track battery system dynamics.
- Validated the approach with battery experimental data for SoC and SoH estimations.

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ABSTRACT

Prognostics and health management (PHM) is an emerging engineering discipline that diagnoses and predicts how and when a system will degrade its performance and lose its partial or whole functionality. Due to the complexity and invisibility of rules and states of most dynamic systems, developing an effective approach to track evolving system states becomes a major challenge. This paper presents a new self-cognizant dynamic system (SCDS) approach that incorporates artificial intelligence into dynamic system modeling for PHM. A feed-forward neural network (FFNN) is selected to approximate a complex system response which is challenging task in general due to inaccessible system physics. The trained FFNN model is then embedded into a dual extended Kalman filter algorithm to track down system dynamics. A recursive computation technique used to update the FFNN model using online measurements is also derived. To validate the proposed SCDS approach, a battery dynamic system is considered as an experimental application. After modeling the battery system by a FFNN model and a state-space model, the state-of-charge (SoC) and state-of-health (SoH) are estimated by updating the FFNN model using the proposed approach. Experimental results suggest that the proposed approach improves the efficiency and accuracy for battery health management.

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1. Introduction

Prognostics and health management (PHM) for machinery has attracted researchers' and industrial companies' attention in recent decades. A wide variety of tools and techniques for PHM have been developed and reported that explore new theories and are implemented in practical applications. Most commonly, PHM is defined as a synthesized science employing a series of tools and techniques to assess the health condition of an operating system, predict its remaining useful life (RUL) in real-time, and reduce catastrophic failures with failure mitigation/recovery actions [1]. PHM carries out two specific tasks for the health management of an operating system over its life cycle: (i) PHM collects sensory signals from the system, extracts from the sensory signals health-relevant features and system characteristics, and diagnoses system faults and degradation; and (ii) PHM captures the system degradation trend based on the current and previous health conditions of the system, and predicts its future health condition and RUL.

Several algorithms and techniques have been developed in the literature for system modeling and prognostics applications by researchers. As a statistical model, autoregressive moving average

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(ARMA) model has been applied to investigating system modeling and predicting future behavior of systems based on time- or cycle-based signal data [2]. Fuzzy logic offers another way to describe systems in the presence of uncertain and unclear data. Instead of gaining a full understanding of the underlying mechanisms of a system, fuzzy logic is dedicated to exploring complex systems in a high level of abstraction in order to develop a decision making system [3–6]. Another technique that has received great attention from researchers is artificial neural networks (ANN). By imitating the structures and mechanisms of neural networks in human brain, an ANN, which connects multiple layers of artificial notes together to form a network, is capable of modeling a complex system without the need of expert knowledge of the system's internal workings. Due to its data-driven nature, the ANN has been successfully employed and developed to model complex systems for various applications [7–9]. As a state-of-the-art classification and regression methodology, support vector machine (SVM) has been very widely used to solve diagnostic and prognostic problems [10]. By using a kernel function, SVM implicitly maps its low dimensional inputs to a high dimensional feature space, which essentially transforms a low dimensional nonlinear problem to a high dimensional linear problem. With the regulation of the KKT conditions (Karush–Kuhn–Tucker conditions), SVM extracts a series of support vectors in the high dimensional feature space from the training data and uses these support vectors to build the classification or regression equations. Another data-driven approach, Gaussian process (GP) regression, provides a very powerful solution for system regression. It has been used in various applications in the PHM field [11,12]. All of the above algorithms are data-driven approaches which only rely on pure data collected from system parameters and measurements. However, if a system model (or a physics-based model) is clearly defined based on physical laws, the Bayesian based approaches are much more dominated solution in practical applications. The most outstanding approach is Markov chain Mote Carlo (MCMC) method, which is a simulation-based method commonly applied in several applications with physics-based models [13–15].

With the increase in system complexity, it has become more difficult to model a complex system through the use of an analytical physics-based model in many practical applications. Data-driven approaches, as mentioned earlier, provide an alternative way to model the complex system relying exclusively on the measured data rather than the underlying physics of the system. However, as the system evolves and degrades over time, a data-driven model trained using historical data may lose accuracy and become less predictive. A commonly used strategy to resolve this issue is to incorporate the most recent data set into the original training data set and refine the data-driven model using the augmented training data set. As a result, the refined model more accurately predicts the most recent behavior of the system. Although this strategy attempts to adaptively refine the data-driven model by updating the training data set, it is still far from being applied in practice due to two obvious shortcomings. First, retraining a data-driven model is time-consuming and of low computational efficiency. In cases where a massive amount of data is continuously being collected and the system is evolving rapidly over time, the retraining would be too slow for the retained model to keep up with the system evolution. The second issue arises when only a negligibly small amount of new data is added to a large training set and, due to the dominance of historical data, the retraining is unable to effectively update the model to reflect the most recent system behavior.

A state-space representation is a powerful mathematical tool for estimating the hidden states (e.g., health condition and performance) of a dynamic system from the system's visible states (e.g., pressure and temperature) that can be measured with sensors. A state-space model consists of a transition function which describes the evolution of states of a system and an observation function which represents the relations between observations and states of the system. As a time-domain approach, the state-space model is effective in addressing a dynamic system problem. Several online estimation techniques have been developed based on the state-space model to track the hidden states of a dynamic system over time. Kalman filter (KF) and particle filter (PF) are representative of these techniques [16–20]. Even though the online estimation techniques are capable of achieving accurate tracking of system hidden states, their use is largely limited by the aforementioned difficulties in modeling a complex dynamic system.

To address the above challenges, this paper proposes a self-cognizant dynamic system (SCDS) approach. By combining the advantages of both data-driven approaches and online estimation techniques, the proposed SCDS approach not only resolves the low efficiency and accuracy issues of data-driven approaches due to the evolving system behavior, but also eliminates the dependency of online estimation techniques on the physics-based modeling of the dynamic system. The main idea of the proposed approach is the integration of an intelligent system modeler with an online estimator to build a self-cognizant dynamic system. The intelligent system modeler closely monitors and learns the dynamic system behavior, and actively seeks adaptations of the dynamic system model to better emulate the system behavior. The online estimator not only estimates the hidden states based on the measured and predicted visible states, but also updates the intelligent system modeler by using online observations, in order to gain a better understanding of the dynamic system. To implement the self-cognizant dynamic system, this work employs a feed-forward neural network (FFNN), the basic architecture of ANN, as the intelligent system modeler and a dual extended Kalman filter (DEKF), the nonlinear version of KF for dual state estimation, as the online estimator. The FFNN allows for the intelligent adaptation of the system model to the changing dynamic system, while the DEKF enables the dual estimation of two hidden states, namely the state and model parameters.

The rest of this paper is organized as follows. Section 2 presents the theoretical foundation the numerical implementation of the proposed SCDS approach. Section 3 introduces the background of a lithium-ion (Li-ion) battery system and applies the SCDS approach to addressing state of charge (SoC) and state of health (SoH) estimation. Section 4 presents an experimental case study to demonstrate the effectiveness of the SCDS approach in Li-ion battery health management. A brief conclusion and future work are provided in Section 5.

2. Self-cognizant dynamic system approach

This section introduces the proposed SCDS approach. Section 2.1 presents the structure of a self-cognizant dynamic system. Section 2.2 discusses the implementation of the SCDS approach using the DEKF technique and the FFNN model.

2.1. Structure of self-cognizant dynamic system

Fig. 1 depicts the structure of a self-cognizant dynamic system, which includes a dynamic system and a self-cognizant system. The goal of the self-cognizant system is to perceive the dynamic system with the help of an intelligent system modeler and an estimator. The hidden states (e.g., health condition and performance) of the dynamic system cannot be sensed by the self-cognizant system, while the visible states (e.g., pressure and temperature) that are affected by the hidden states can be measured using sensors. By utilizing the measurable visible states of the dynamic system, the

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