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A data-model-fusion prognostic framework for dynamic system state forecasting

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ABSTRACT

A novel data-model-fusion prognostic framework is developed in this paper to improve the accuracy of system state long-horizon forecasting. This framework strategically integrates the strengths of the data-driven prognostic method and the model-based particle filtering approach in system state prediction while alleviating their limitations. In the proposed methodology, particle filtering is applied for system state estimation in parallel with parameter identification of the prediction model (with unknown parameters) based on Bayesian learning. Simultaneously, a data-driven predictor is employed to learn the system degradation pattern from history data so as to predict system evolution (or future measurements). An innovative feature of the proposed fusion prognostic framework is that the predicted measurements (with uncertainties) from the data-driven predictor will be properly managed and utilized by the particle filtering to further update the prediction model parameters, thereby enabling markedly better prognosis as well as improved forecasting transparency. As an application example, the developed fusion prognostic framework is employed to predict the remaining useful life of lithium ion batteries through electrochemical impedance spectroscopy tests. The investigation results demonstrate that the proposed fusion prognostic framework is an effective forecasting tool that can integrate the strengths of both the data-driven method and the particle filtering approach to achieve more accurate state forecasting.

1. Introduction

Condition-based maintenance is a program that recommends maintenance decisions based on the information collected through system condition monitoring (or system state estimation) and equipment failure prognostics (or system state forecasting), in which prognostics still remains as the least mature element in both research and real-world applications (Jardine et al., 2006). Prognostics entails the use of the current and previous system states (or observations) to predict the future states of a dynamic system. Reliable forecast information can be used to schedule repairs and maintenance in advance and provide an alarm before faults reach critical levels so as to prevent machinery performance degradation, malfunction, or even catastrophic failures (Liu et al., 2009).

In general, prognostics can be conducted using either data-driven methods or model-based approaches. Data-driven methods use pattern recognition and machine learning to detect changes in system states (Yagiz et al., 2009; Gupta and Ray, 2007). The classical data-driven methods for nonlinear system prediction include the use of stochastic models such as the autoregressive (AR) model, the threshold AR model (Tong and Lim, 1980), the bilinear model (Subba, 1981), the projection pursuit (Friedman and Stuetzle, 1981), the multivariate adaptive regression splines (Friedman, 1991), and the Volterra series expansion (Brillinger, 1970). Since the last decade, more research interests in data-driven system state forecasting have been focused on the use of flexible models such as various types of neural networks (NNs) (Atiya et al., 1999; Liang and Liang, 2006) and neural fuzzy (NF) systems (Husmeier, 1999; Korbicz, 2004; Jang, 1993). Data-driven methods rely on past patterns of the degradation of similar systems to project future system states; their forecasting accuracy depends on not only the quantity but also the quality of system history data, which could be a challenging task in many real applications (Liu et al., 2009;

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Wang and Vrbanek, 2008). Another principal disadvantage of data-driven methods is that the prognostic reasoning process is usually opaque to users (Tse and Atherton, 1999); consequently, they are not suitable for some advanced applications where forecast reasoning transparency is required (e.g., credit card cheating, earthquake and stock market prediction).

Model-based approaches typically involve building models (or mathematical functions) to describe the physics of the system states and failure modes; they incorporate physical understanding of the system into the estimation of system state and/or remaining useful life (RUL) (Adams, 2002; Luo et al., 2003; Chelidze and Cusumano, 2004). Model-based approaches, however, may not be suitable for many industrial applications where the physical parameters and fault modes may vary under different operation conditions (Pecht and Jaai, 2010). On one hand, it is usually difficult to tune the derived models in situ to accommodate time-varying system dynamics. On the other hand, model-based approaches cannot be used for complex systems whose internal state variables are inaccessible (or hard) to direct measurement using general sensors. In this case, inference has to be made from indirect measurements using techniques such as particle filtering (PF). The PF-based approaches have been used for prognostic applications (Saha et al., 2009), in which the PF is employed to update the nonlinear prediction model and the identified model is applied for system state forecasting. However, a limitation associated with the classical PF-based predictors is that the prediction model parameters cannot be updated during the prognostic period since no new measurements are available. The prediction accuracy could be low in many applications because the identified model during the state estimation period may not be accurate and robust.

To address the aforementioned challenges, a data-model-fusion framework is proposed in this work for system state prognostics. The developed framework aims to integrate the strengths of the data-driven prognostic method and the model-based PF approach for a more reliable system state forecasting. The proposed fusion framework is new in the following aspects: (1) the prediction uncertainties from the data-driven predictor can be properly managed and utilized through the fusion framework so as to further update the prediction model parameters; (2) the fusion prognostic framework can overcome the aforementioned limitations of both the data-driven method and the model-based PF approach so as to make prediction models more interpretable and transparent; (3) as an application example, the developed fusion prognostic framework is implemented for the RUL prediction of lithium-ion batteries.

This paper is organized as follows. The proposed fusion prognostic framework is described in Section 2. The effectiveness of this fusion framework is demonstrated in Section 3 via an application in battery RUL prediction. A summary of important observations and conclusive remarks are given in Section 4.

2. The fusion prognostic framework for dynamic system state forecasting

In this section, we first briefly discuss two principal components of the proposed fusion prognostic framework: the data-driven prognostic method and the PF-based prognostic approach. The limitations of each component will be examined, which, in turn, motivates the advanced research of this work. The fusion prognostic framework will then be described. This framework aims to integrate the advantages of both the data-driven predictor and the PF approach while alleviating their respective limitations, so as to develop a more reliable system state forecasting paradigm.

2.1. The data-driven prognostic method

Data-driven predictors employ pattern recognition and machine learning to forecast changes in system states (Yagiz et al., 2009; Gupta and Ray, 2007). Since the last decade, more research interests in data-driven system state forecasting have shifted to the use of flexible models such as NNs (Atiya et al., 1999; Husmeier, 1999), NF systems (Jang, 1993), and recurrent neural fuzzy (RNF) systems (Liu et al., 2009). The authors' research group has also developed several data-driven predictors for machinery applications (Liu et al., 2009; Wang and Vrbanek, 2008), and the investigation results have shown that if an NF predictor is properly trained, it performs better than both the feedforward and the recurrent NN forecasting schemes. The prediction output of a data-driven predictor can be generally described as

$$Y_k = g(C_{1:q}, Y_{1:k-1}) + u_k, \tag{1}$$

where Y_k is the predicted measurement at step k, $Y_{1:k-1}$ is the system's historical measurements up to time step $k-1$, $C_{1:q}$ are the system inputs (or system operational conditions), $g(\cdot)$ denotes the nonlinear prediction reasoning, and u_k is a random noise that represents the prediction uncertainty. The uncertainty term u_k generally pertains to the specific data-driven prognostic scheme (i.e., the structure and training algorithm) as well as the quality and quantity of training data, which can be estimated through a large number of simulations (Tiwari and Chatterjee, 2010).

Although data-driven prognostic methods have demonstrated some superior properties to other classical forecasting tools, they still have some limitations in industrial applications (Walter and Pronzato, 1997): (1) the forecasting accuracy strictly depends on if the training data are adequate and representative of all the possible application conditions. Such a requirement is usually difficult to achieve in real-world applications because, on one hand, running a system to failure could be a lengthy and rather costly process and the training data are usually inadequate in industrial applications; on the other hand, most machines/systems operate in noisy and/or uncertain environments and machinery dynamic characteristics may change suddenly (e.g., just after repairs or regular maintenance), thus the training data cannot cover all the possible operational conditions. (2) For NN/NF-based predictors, the forecasting reasoning structures are usually difficult to be understood by users. This limits their applications in which reasoning transparency (or understandability) is required. (3) The prediction uncertainty u_k usually increases dramatically as the prediction step becomes larger; as a result, an appropriate filtering process is required to further improve the forecasting accuracy. The aforementioned limitations associated with data-driven prognostic methods can be properly alleviated through the proposed data-model-fusion framework, which will be discussed in Section 2.3.

2.2. The particle filtering-based prognostic approach

For complex systems whose internal state variables are inaccessible (or hard) to direct measurement using general sensors, inference has to be made from indirect measurements, for which Bayesian learning provides a rigorous framework. Given a general discrete-time state estimation problem, the unobservable state vector $X_k \in R^n$ evolves according to the following system model

$$X_k = f(X_{k-1}) + w_k, \tag{2}$$

where $f: R^n \to R^n$ is the system state transition function and $w_k \in R^n$ is a noise whose known distribution is independent of time. At each discrete time instant, an observation (or measurement) $Y_k \in R^p$ becomes available. This observation is related to the unobservable state vector via the observation equation

$$Y_k = h(X_k) + v_k, \quad (3)$$

where $h:R^n \to R^p$ is the measurement function and $v_k \in R^p$ is another noise whose known distribution is independent of the system noise and time. The Bayesian learning approach to system state estimation is to recursively estimate the probability density function (pdf) of the unobservable state X_k based on a sequence of noisy measurements $Y_{1:k}$, $k=1,\ldots,K$. Assume that X_k has an initial density $p(X_0)$ and the probability transition density is represented by $p(X_k|X_{k-1})$. The inference of the property of the states X_k relies on the marginal filtering density $p(X_k|Y_{1:k})$. Suppose that the density $p(X_{k-1}|Y_{k-1})$ is available at step $k-1$. The prior density of the state at step k can then be estimated via the transition density $p(X_k|X_{k-1})$,

$$p(X_k|Y_{1:k-1}) = \int p(X_k|X_{k-1})p(X_{k-1}|Y_{1:k-1})\mathrm{d}X_{k-1}. \quad (4)$$

Correspondingly, the marginal filtering density is computed via the Bayes' theorem,

$$p(X_k|Y_{1:k}) = \frac{p(Y_k|X_k)p(X_k|Y_{1:k-1})}{p(Y_k|Y_{1:k-1})}, \quad (5)$$

where the normalizing constant is determined by

$$p(Y_k|Y_{1:k-1}) = \int p(Y_k|X_k)p(X_k|Y_{1:k-1})\mathrm{d}X_k. \quad (6)$$

Eqs. (4)–(6) constitute the formal solution to the Bayesian recursive state estimation problem. If the system is linear with Gaussian noise, the above method reduces to the Kalman filter. For nonlinear/non-Gaussian systems, there are no closed-form solutions and thus numerical approximations are usually employed (Simon, 2006).

The PF is a technique for implementing the recursive Bayesian filtering via Monte Carlo simulations, whereby the posterior density function $p(X_k|Y_{1:k})$ is represented by a set of random samples (particles) $X_k^1,\ldots,X_k^M$ and their associated weights $\pi_k^1,\ldots,\pi_k^M$, that is,

$$p(X_k|Y_{1:k}) \approx \sum_{i=1}^{M} \pi_k^i \delta(X_k - X_k^i), \qquad \sum_{i=1}^{M} \pi_k^i = 1, \quad (7)$$

where M is the number of particles, the weights π_k^i can be recursively updated using the importance sampling with an importance density $G(X_k|X_{k-1}^i,Y_k)$,

$$\pi_k^i \propto \pi_{k-1}^i \frac{p(Y_k|X_k^i)p(X_k^i|X_{k-1}^i)}{G(X_k^i|X_{k-1}^i,Y_k)}. \quad (8)$$

When the importance density is approximated as $p(X_k|X_{k-1})$, (8) becomes

$$\pi_k^i \propto \pi_{k-1}^i p(Y_k|X_k^i). \quad (9)$$

In implementation, resampling is applied in every single step to obtain equally-weighted samples so as to avoid the degeneracy problem of the algorithm (Douc et al., 2005).

The PF-based approaches have been used for prognostic applications (Saha et al., 2009), in which the PF is employed to identify the nonlinear prediction model parameters during the state estimation period. The identified model is then applied for system state forecasting. However, a limitation associated with these classical PF-based predictors is that the prediction model parameters cannot be updated during the prognostic period. As a result, the identified model may not be accurate and robust, and the prediction accuracy could be low in many applications, especially in long-horizon forecasting with limited measurements. This limitation associated with the classical PF-based prognostic approach, however, can be properly alleviated through the proposed data-model-fusion framework, which will be described in the following subsection.

2.3. The proposed data-model-fusion prognostic framework

Both the data-driven prognostic method and the model-based PF approach have their own strengths and limitations in prognostic applications. The proposed fusion prognostic framework aims to integrate these two methods in a manner that can take the strengths of each approach while overcoming their respective limitations. To achieve this goal, the fusion prognostic framework incorporates the data-driven prediction into the PF learning structure, such that the predicted future measurements (with uncertainty u_k) from the data-driven predictor can be properly managed and utilized by the PF approach so as to keep updating the system model parameters during the prognostic period, thereby resulting a more reliable system state forecasting.

The schematic diagram of system condition (or state) monitoring and prognostics is shown in Fig. 1. The diagnostic routine starts with data acquisition using sensors and data acquisition boards (i.e., Sensor/Data) (Pecht and Jaai, 2010). Appropriate signal processing techniques will then be applied to extract representative features and/or system model parameters from the collected data (i.e., Feature Extraction) (Eren and Devaney, 2004; Wang and Gao, 2003; Yu, 2011). These features will be used to determine the health condition of the system (i.e., Healthy Baseline). Health condition monitoring is performed to track the degradation trajectories of these features (i.e., In-Situ

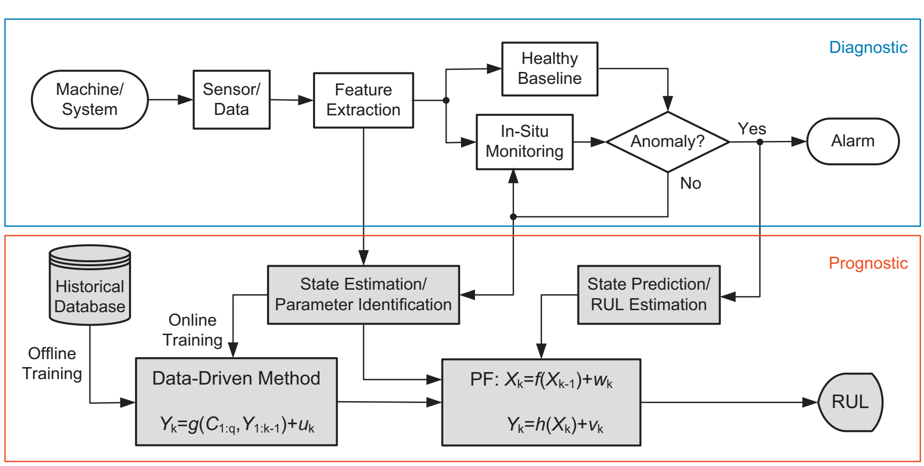

Fig. 1. The schematic diagram of the system condition monitoring and prognostics.

Monitoring). It should be noted that feature extraction plays a significant role for system health condition monitoring, whereas non-robust features may lead to false alarms (i.e., an alarm is triggered by some noise instead of a real system fault) or missed alarms (i.e., the monitoring tool cannot recognize the existence of a system defect) in diagnostic operations. In general, different signal processing techniques are required to extract representative features in different applications; this issue will not be discussed in this paper. Interested readers can refer to (Liu et al., 2008; Goebel et al., 2008) for more information about feature extraction. Once the degradation trajectories of the features (or some system model parameters) reach the predetermined thresholds, an alarm will be generated to indicate that a fault has been detected, which then triggers the prognostic routine.

The subsequent system state prognostics will be conducted through the proposed data-model-fusion framework. First, the selected data-driven predictor is off-line trained using some history data collected from systems with similar degradation trajectories (i.e., Offline Training). The initially-trained data-driven predictor will then be tuned using the available data from the target system so as to accommodate the new system dynamics (i.e., Online Training). The training of the data-driven predictor can be conducted using appropriate recursive learning algorithms (e.g., the recursive Levenberg–Marquardt method developed by the authors' research group (Liu et al., 2009)). The system prediction model with unknown (or initial/empirical) model parameters is then fed into the PF learning structure, as per (2) and (3). The PF will perform state estimation in parallel with model parameter identification in a recursive manner as new observations (or measurements) become available. The interactive mechanics between the data-driven predictor and the model-based PF approach is given below. Suppose the prognostic routine starts from step $k-1$. First, the data-driven predictor is applied to forecast the next measurement Y_k, where $Y_k = g(C_{1:q}, Y_{1:k-1}) + u_k$, as per (1). The predicted measurement Y_k is then incorporated into the PF learning structure as a new observation, which can be used to update the prediction model parameters (i.e., X_k). In this process, the prediction uncertainty u_k of the data-driven predictor is incorporated into the PF measurement function by

$$g(C_{1:q}, Y_{1:k-1}) = h(X_k) + (\nu_k - u_k). \tag{10}$$

The prediction uncertainty u_k will increase dramatically as the prediction step becomes larger, which can be estimated using the history data through simulations (Tiwari and Chatterjee, 2010). The measurement uncertainty ν_k is related to the sensors, the measurement procedure, the skill of the operator, and the environment; it is usually assumed as a constant pdf in applications (Simon, 2006). The forecast measurements $g(C_{1:q}, Y_{1:k-1})$ from the data-driven predictor will thus be properly utilized by the PF through the Bayesian learning (as discussed in Section 2.2), such that the prediction model parameters can be updated in a continuous and recursive manner, thereby resulting a more accurate system state forecasting. In Section 3, the proposed data-model-fusion prognostic framework will be applied for the RUL prediction of lithium-ion batteries, which serves as an application example to future enhance the understandability of the proposed fusion framework and also to verify its viability.

3. Performance evaluation

The effectiveness of the proposed fusion prognostic framework is examined through an application in battery RUL prediction. Its performance will be compared with the related classical PF-based prognostic method and three data-driven predictors based on the feedforward NN, the NF paradigm, and the RNF scheme. Batteries are widely used in various engineering and household systems. An effective prognostic tool is critically needed to estimate the health conditions of a battery and predict its RUL. The predicted battery RUL information can be used not only for preventing performance degradation of the related equipment, but also for scheduling battery recharge and replacement, which is critical in many applications such as the emerging electric cars and aerospace vehicles.

Dynamic models have been built for health management and RUL prediction of lithium ion batteries (Gao et al., 2002). These models take into account nonlinear equilibrium potentials, rate and temperature dependencies, thermal effects, and transient power response. However, it still remains a challenge to accurately predict the RUL of a battery using a model-based approach when environmental and operating conditions change. Furthermore, modeling a lithium-ion battery from the first principles of the internal electrochemical reactions can be very tedious and computationally intractable. The PF-based prognostic was investigated by the Prognostics Center of Excellence at NASA Ames Research Center (Saha et al., 2009). A lumped parameter model was used to characterize the inside chemistry of batteries though a simple electrical circuit, as shown in Fig. 2, where R_E denotes the electrolyte resistance, R_{CT} is the charge transfer resistance, R_W is the Warburg impedance, and C_{DL} is the dual layer capacitance. The change in resistive components of the circuit can be used to explain the deterioration in battery capacity.

The battery RUL is estimated in terms of capacity degradation. The failure threshold is usually defined by the manufacturer for specific applications. Generally, a lithium-ion battery is deemed to fail when its capacity $C/1$ fades by 30% of the rated value (Liu et al., 2010). The batteries' capacity, however, is usually inaccessible through direct measurements; therefore, the lumped parameters R_E and R_{CT} are employed for battery RUL prediction. $R_E + R_{CT}$ is typically inversely proportional to the capacity $C/1$ and can be estimated through the electrochemical impedance spectroscopy test (Saha et al., 2009). The battery prediction model (with unknown parameters) is described as follows:

$$\begin{aligned}
&Z_0 = \Phi; \quad \Lambda_0 = \Lambda \\
&Z_k = Z_{k-1}\exp\Lambda_k + w_k \\
&\Lambda_k = \Lambda_{k-1} + \upsilon_k \\
&X_k = [Z_k;\ \Lambda_k] \\
&Y_k = Z_k + \nu_k
\end{aligned} \tag{11}$$

where the vector Z denotes battery parameters $R_E + R_{CT}$, and Φ and Λ are exponential growth model parameters. The Z and Λ vectors are combined to form the state vector X. The measurement vector Y consists of the battery parameters (i.e., $R_E + R_{CT}$) inferred from measurements. The parameter Φ takes the initial value of $R_E + R_{CT}$. The value of Λ is recursively updated, whose initial value is derived from the training data using a least-square estimator. The vectors w, υ, and ν are zero-mean Gaussian noise.

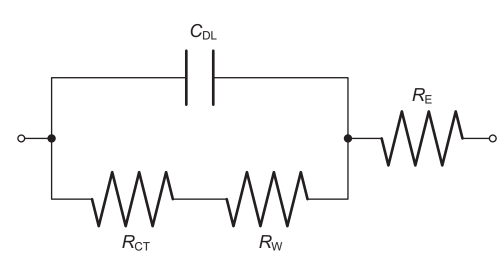

Fig. 2. Lumped parameter model of a lithium ion battery.

3.1. Battery RUL prediction using data-driven prognostic methods

In this comparison study, three data-driven predictors, based on the feedforward NN, the NF and the RNF schemes (Liu et al., 2009), will be applied for battery RUL prediction. Each predictor has five inputs in this case. The RNF predictor is a hybrid model of direct, adaptive and recursive predictions and its network architecture is schematically shown in Fig. 3. This RNF predictor is constructed based on a feedforward NF paradigm with recurrent feedback links in the second and third layers. The network output is adaptively fed back to the input layer to represent temporal information spatially. The NF predictor has the same structure as the RNF predictor but without these recurrent feedback links. The nonlinear parameters in both the RNF and NF predictors (i.e., the membership function parameters and/or feedback link weights) are trained using the recursive Levenberg–Marquardt method, whereas the linear parameters (i.e., the parameters in the consequents) are optimized by using the recursive least-square estimate method (Liu et al., 2009). The feedforward NN predictor has two hidden layers with each layer having four nodes; it is trained using the Levenberg–Marquardt method as well. It is worth mentioning that the recursive Levenberg–Marquardt method was developed in (Liu et al., 2009) for training the nonlinear parameters in neural networks or neural fuzzy systems. This technique has been applied for the sunspot activity forecasting, Mackey–Glass data forecasting and gear health condition forecasting (Liu et al., 2009). Testing results have shown that this network training method has a better capability than the classical gradient descent-based methods in escaping from the local minima. Accordingly in this work, we have applied this recursive Levenberg-Marquardt training method for battery life prediction.

The data R_E+R_{CT} used in this study were from the second generation, Gen 2, 18650-size lithium-ion cells that were cycle-life tested at different temperatures (Saha et al., 2009; Liu et al., 2010). The data-driven predictors are trained using the history data of R_E+R_{CT}. Since the temperature plays an important role in determining charge retention capacity of a battery, it is used as a network input to facilitate prediction of battery RUL at different temperatures. The maximum adaptive output feedback depth for all three data-driven predictors is set to three. The trained data-driven predictors are employed to forecast an unknown trajectory of R_E+R_{CT} collected at 45 °C. Predictions are generated continuously from week 20 to week 64 at every four weeks' interval. For each prediction, 50 program runs are taken to obtain 50 trajectories of R_E+R_{CT}. Fig. 4 shows examples of the forecasting results, respectively, from the implemented RNF predictor (Fig. 4(a)), the NF predictor (Fig. 4(b)), and the NN predictor (Fig. 4(c)), in which the prediction is triggered at week 20. It is seen that the prediction means from these 50 trajectories of R_E+R_{CT} cannot properly track the true trajectory and the prediction error (or uncertainty) rises as the prediction step increases. The poor forecasting performance from these data-driven predictors are mainly because the available data of R_E+R_{CT} in this work for network training are quite limited (Liu et al., 2010). As can be seen from Fig. 4, the batteries usually took more than a year to age, and running such a system to failure in a lab environment is a tedious and costly process. The prediction uncertainty from the data-driven predictors, however, can be properly managed and utilized through the proposed fusion prognostic framework so as to further improve the forecasting accuracy, which will be demonstrated in the following subsection.

3.2. Battery RUL prediction using the PF-based method and the fusion prognostic framework

The developed fusion prognostic framework takes two steps to perform the prognostics: current state estimation and future state forecasting. During the state estimation period, the fusion framework performs system state estimation in parallel with model parameter identification based on the true R_E+R_{CT} measurements. During the state forecasting period, the identified model parameter (i.e., Λ in this case) can be further tuned based on the predicted system evolution (or future measurements) from the data-driven predictor. By tests, the uncertainty term (ν_k-u_k) associated with these data-driven predictions is characterized in this work by a zero-mean Gaussian noise with an increasing

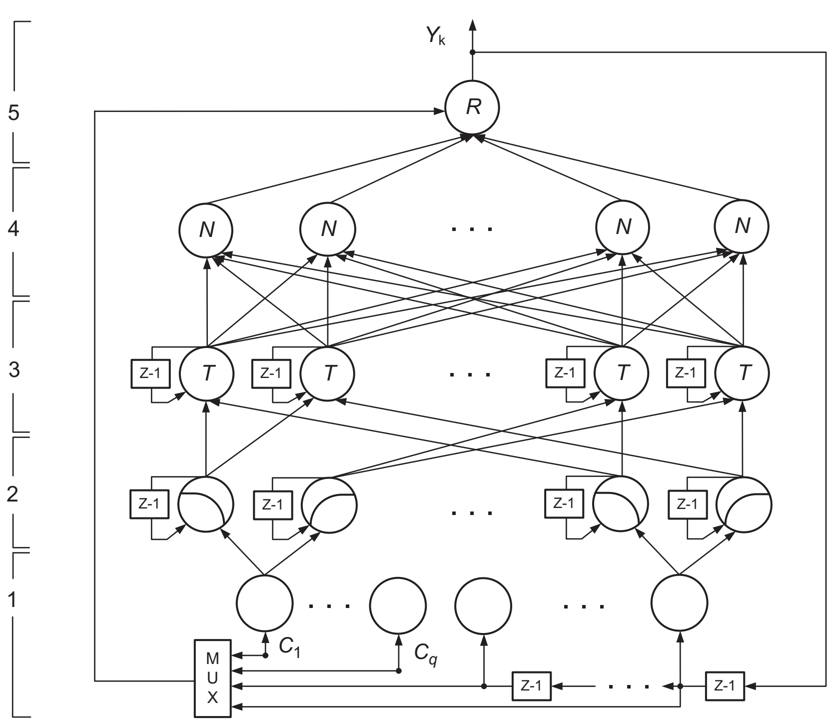

Fig. 3. The network architecture of the RNF system.

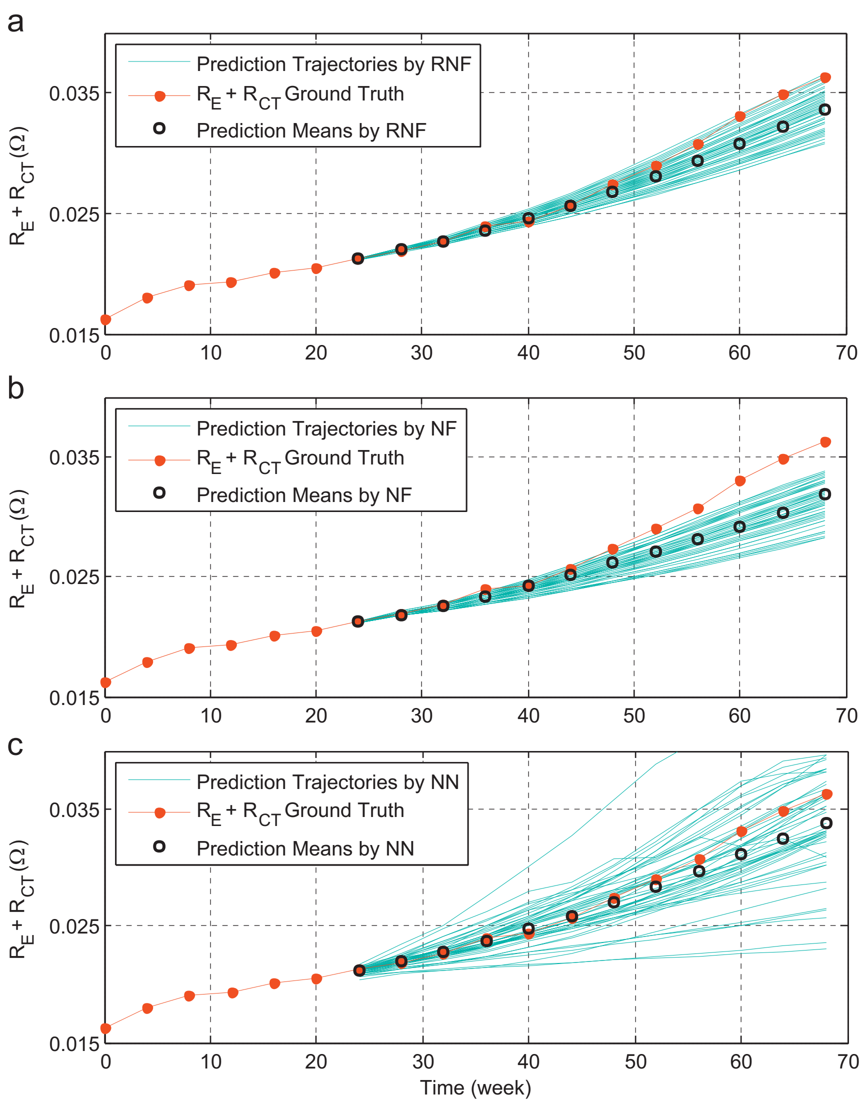

Fig. 4. The forecasting results at week 20 using three data-driven predictors: (a) the RNF predictor; (b) the NF predictor; (c) the NN predictor.

standard deviation given as $0.005\Phi3^{(k-K_t)}$, where k is the iteration step and K_t is the step index at which the first prognostic is triggered. As a comparison, the classical PF-based predictor is also implemented for this application. In each iteration, a total of $M=1000$ particles are employed for processing this 2-dimensional problem. Fig. 5(a) shows the respective state tracking and future state forecasting for the battery parameter R_E+R_{CT} when the RNF predictor and the PF are fused through the proposed data-model-fusion framework. The prognostic is initiated at week 20. It can be seen that the proposed fusion framework can provide a more accurate forecasting for the battery parameter R_E+R_{CT} than both the RNF predictor and the classical PF-based predictor. Fig. 5(b) shows the estimation of the corresponding model parameter Λ. It can be seen that Λremains constant in prognosis when the classical PF-based predictor is employed, whereas the proposed fusion prognostic framework can keep updating this parameter by adaptively incorporating the available forecast information from the RNF predictor. By a linear transformation, the derived capacities are plotted in Fig. 6, in which the shaded area represents the distribution of the predicted RULs over 100 program runs. The RUL threshold is chosen to be 70% of the rated capacity. The proposed fusion prognostic framework yields an RUL error of 1.59 weeks early, which outperforms both the classical PF-based predictor (33.25 weeks late) and the RNF predictor (4.18 weeks late).

Fig. 7 shows the testing results when the PF and the NF predictor are fused by using the proposed fusion prognostic framework. The fusion framework yields an RUL error of 0.23 weeks early, which is much more accurate than both the classical PF-based predictor (33.70 weeks late) and the NF predictor (7.55 weeks late). Likewise, Fig. 8 illustrates the processing results when the PF and the NN predictor are fused by using the proposed fusion prognostic framework. It is obvious that the proposed fusion framework can achieve a more accurate state forecasting (2.25 weeks early) than the classical PF-based predictor (32.81 weeks late) and the NF predictor (3.94 weeks late).

The results shown in Figs. 5–8 are obtained when the prediction is triggered at week 20. Actually in our tests, the predictions are triggered anytime between week 20 and week 60 at a four-week interval. The $\alpha-\lambda$ prognostic metric (Saxena et al., 2010) is employed to quantify the prognostic performance, in this case, $\alpha=0.1$ (i.e., 10% prediction error or 90% prediction accuracy) and $\lambda=0.5$ (i.e., 50% remaining time from the earliest prediction to the actual end-of-life of a battery). Figs. 9–11 show the predicted battery RULs from the proposed fusion prognostic framework, the classical PF-based predictor, and three data-driven predictors. It

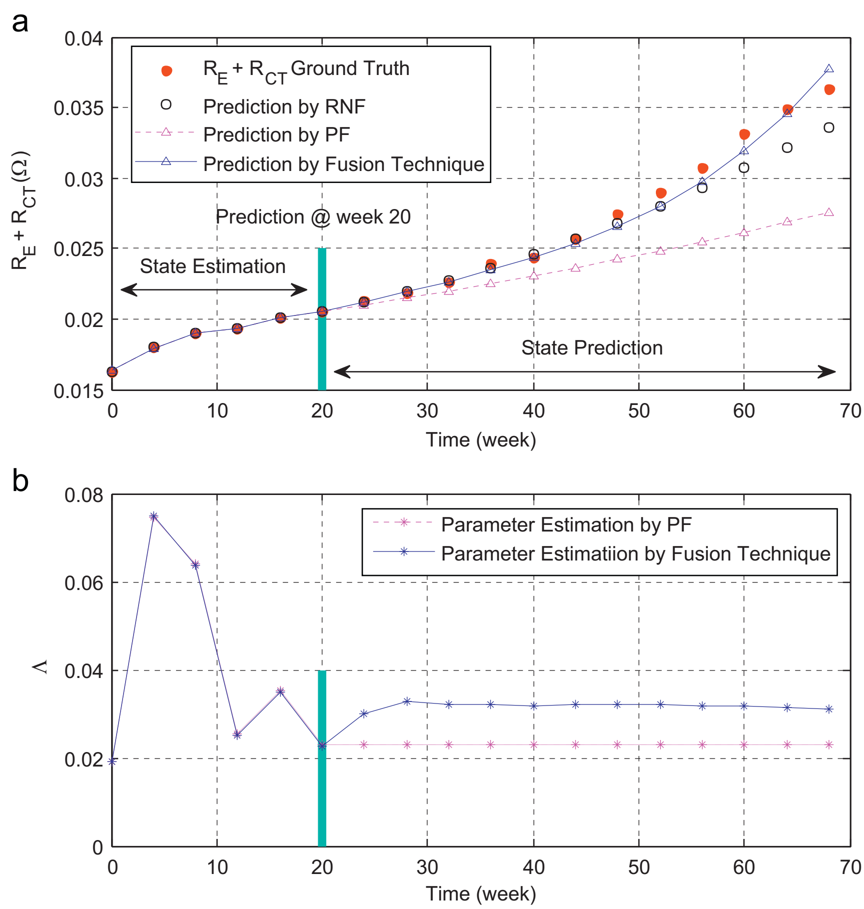

Fig. 5. (a) State tracking and future state prediction at week 20 for the battery parameter R_E+R_{CT} by using the proposed fusion prognostic framework (triangles, in blue), the classical PF-based predictor (triangles, in magenta), and the RNF predictor (circles, in black). (b) Parameter Λestimation by using the proposed fusion framework (stars, in blue) and the classical PF-based predictor (stars, in magenta). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

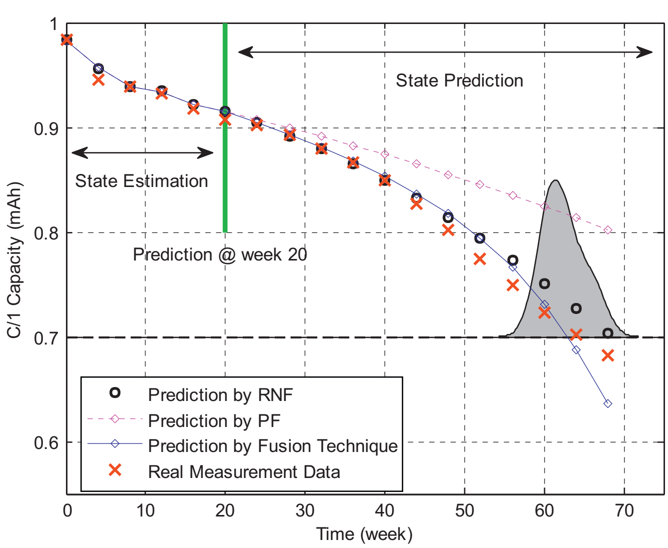

Fig. 6. Battery RUL prediction at week 20 by using the proposed fusion prognostic framework (diamonds, in blue), the classical PF-based predictor (diamonds, in magenta), and the RNF predictor (circles, in black); the distribution (shaded area) of the RULs is evaluated over 100 program runs of the proposed fusion prognostic framework. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

can be seen that the fusion prognostic framework can effectively incorporate all these three data-driven predictors and provide more accurate forecasting on the battery RUL during the first 50% remaining useful time period (i.e., $\lambda=0.5$). Furthermore, the proposed fusion framework can generate an earlier RUL prediction than the other related predictors, which is considered more favorable than a late prediction to avoid some unanticipated failures. The superior prognostic performance of the developed fusion framework over the classical PF-based predictor lies in the fact that the fusion framework is capable of updating the prediction model parameters in a continuous and recursive manner by properly incorporating the available forecast information from the data-driven predictor through the Bayesian learning. It should be noted that a condition based maintenance program usually involves five sequential modules: sensing, feature extraction, fault diagnostics, failure prognostics, and maintenance action. This manuscript focuses on failure prognostics. The fault diagnostic information is only used to trigger the prognostic routine when the feature indices have reached some predetermined thresholds. In this work, these thresholds are assumed to be the values of R_E+R_{CT} at week 20 to week 64, respectively.

4. Conclusions

A data-model-fusion prognostic framework has been developed in this work for system state forecasting. This fusion framework is able to integrate the strengths of both the data-driven prognostic method and the model-based particle filtering in system state prediction while alleviating their respective limitations. A unique feature of the proposed fusion framework is to improve the transparency of the data-driven method in the

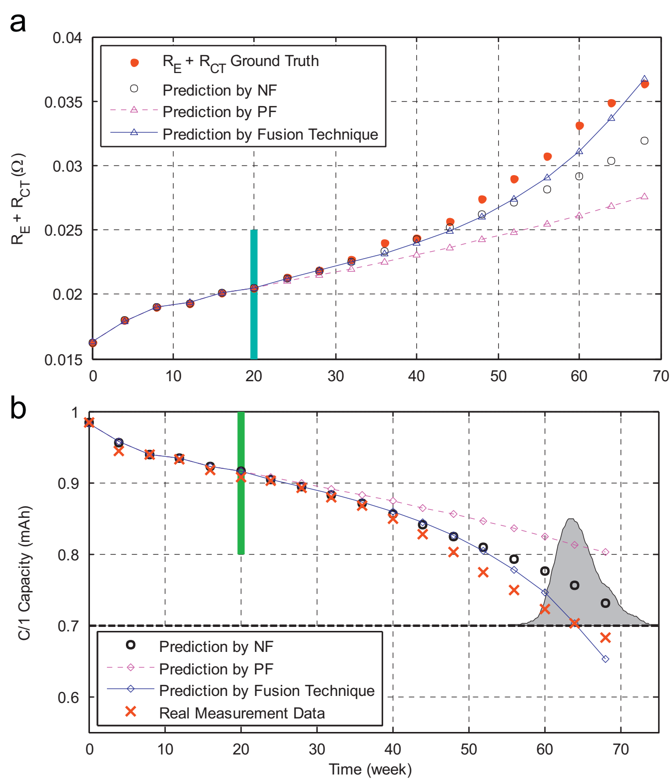

Fig. 7. (a) State tracking and future state prediction at week 20 for the battery parameter R_E+R_{CT} by using the proposed fusion prognostic framework (triangles, in blue), the classical PF-based predictor (triangles, in magenta), and the NF predictor (circles, in black); (b) battery RUL prediction at week 20 by using the proposed fusion prognostic framework (diamonds, in blue), the classical PF-based predictor (diamonds, in magenta), and the NF predictor (circles, in black). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

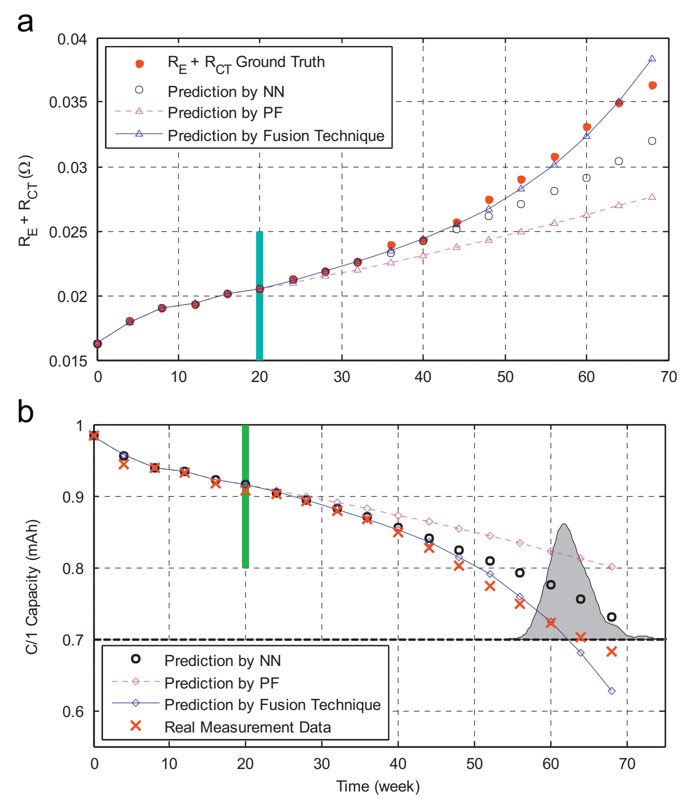

Fig. 8. (a) State tracking and future state prediction at week 20 for the battery parameter R_E+R_{CT} by using the proposed fusion prognostic framework (triangles, in blue), the classical PF-based predictor (triangles, in magenta), and the NN predictor (circles, in black); (b) battery RUL prediction at week 20 by using the proposed fusion prognostic framework (diamonds, in blue), the classical PF-based predictor (diamonds, in magenta), and the NN predictor (circles, in black). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

sense that its prediction uncertainty can be properly managed and utilized by a particle filtering based learning process. As a result, the nonlinear prediction model parameters can be updated in a continuous and recursive manner so as to further improve the prediction accuracy. The effectiveness of the developed fusion prognostic framework has been demonstrated through an application example in predicting the remaining useful life of lithium ion batteries. The test results have indicated that the proposed fusion prognostic framework can effectively track system states by incorporating the predicted measurements from the data-driven predictor so as to adaptively update the prediction model parameters; thereby it outperforms the related data-driven predictors and the classical particle filtering based approaches in system state forecasting.

As a final note, it is also worth mentioning the following considerations: (1) the goal of this paper is to propose a novel data-model fusion framework for prognostic applications. This concept can be analogous to sensor fusion using the extended Kalman filter in the field of fault diagnostics. In implementation, this fusion prognostic framework involves two principal components: a data driven prognostic method by which the uncertainty of the associated data driven forecasting can be estimated, and a particle filtering based system degradation model by which the system aging trend can be interpreted. For different applications, these two components will differ and must be determined. (2) In this work, three data-driven prognostic methods (i.e., the NN predictor, the NF predictor, and the RNF predictor) and a generic particle filtering have been tested. Testing results have shown that the proposed fusion framework outperforms each of these prognostic methods. Actually, it is safe to say that the proposed

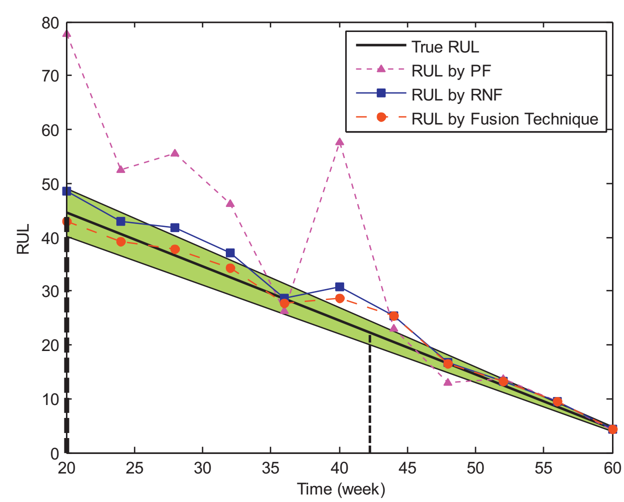

Fig. 9. The battery RULs predicted by the proposed fusion prognostic framework (dots, in red), the classical PF-based predictor (triangles, in magenta), and the RNF predictor (squares, in blue); the shaded green area is the 90% accuracy cone (α=0.1, λ=0.5). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

fusion framework could work well with virtually any data-driven prognostic methods as long as the prediction uncertainty can be estimated. (3) The authors have applied the most commonly-used metric (i.e., the $\alpha-\lambda$ prognostic metric where α is the prediction error andλ is the remaining time from the earliest prediction to

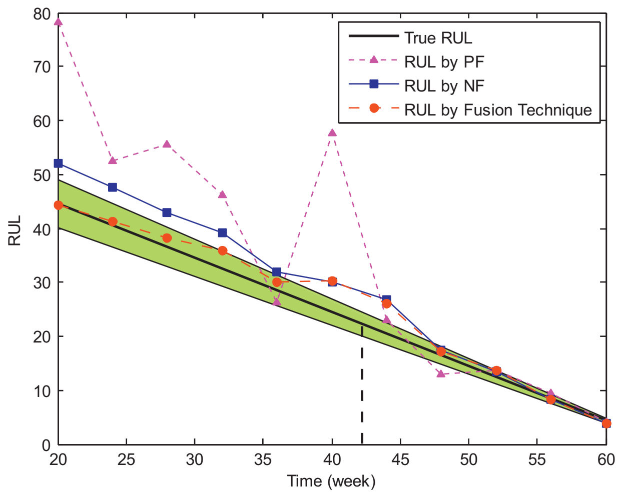

Fig. 10. The battery RULs predicted by the proposed fusion prognostic framework (dots, in red), the classical PF-based predictor (triangles, in magenta), and the NF predictor (squares, in blue); the shaded green area is the 90% accuracy cone ($\alpha=0.1$, $\lambda=0.5$). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

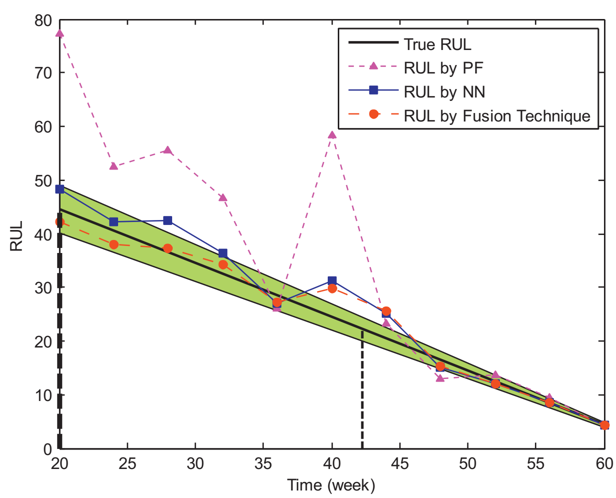

Fig. 11. The battery RULs predicted by the proposed fusion prognostic framework (dots, in red), the classical PF-based predictor (triangles, in magenta), and the NN predictor (squares, in blue); the shaded green area is the 90% accuracy cone ($\alpha=0.1$, $\lambda=0.5$). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

the actual end-of-life of a system) in failure prediction to quantify the prognostic performance of the proposed data-model fusion prognostic framework; (4) The motivation of this work is elaborated in Section 2 in which the limitations of two principal components of the proposed fusion prognostic framework are discussed. This framework aims to integrate the advantages of both the data-driven predictor and the PF approach while alleviating their respective limitations, so as to develop a more reliable system state forecasting paradigm. (5) Battery prediction is employed in this work as an application example to demonstrate the effectiveness of the proposed fusion framework. The authors use this example instead of others because they have been working on battery RUL prediction for a few years and both the experimental data and the physical prediction model for battery RUL prediction are readily available. It is also expected that the readers or other researchers will apply this framework in the areas of their expertise to further investigate its effectiveness. (6) Compared to fault diagnostic, failure prognostic is a much less mature and more challenging research area. One of the main reasons is the lack of sufficient experimental/field data to support fundamental studies for developing proper prognostic models. Taking the lithium ion battery RUL prediction as an example, it usually takes more than a year (Fig. 4) to age a battery in a lab environment. (7) A collaborative research is currently underway among Carleton University, Nanjing University, and National Research Council of Canada to extend this prognostic framework to failure prognostics of auxiliary power units (APUs) of aircrafts. However, considering the complexity of APUs (thus the associated data base), the research work, including the development of both the physical prognostic model, data-driven prognostic model, will take years to finish and the research results will be published in the follow-up publications. (8) The in-depth statistical analysis (as suggested by one of the reviewers) of the proposed prognostic method deserve further investigation and will be conducted when the testing results from the APUs are obtained. (9) The performance comparison of the proposed fusion framework with other related prognostic methods, e.g., Gaussian process regression (Goebel et al., 2008), independent component analysis (Lee et al., 2004), and Gaussian mixture model (Yu and Qin, 2008, 2009), will remain as topics for future studies.

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