Chapter 37
Integrated System Health Management for Environmental Control and Life Support System in Manned-Spacecraft

Fan Li and Yusheng Wang

Abstract This paper addresses the integrated system health management (ISHM) diagnostics and prognostics for a manned spacecraft's environmental control and life-support system (ECLSS), which ensures the safety of astronauts and guarantees space mission success. For the complex system structure, an integrated diagnostics and prognostics method is presented, which allows for the consideration of continuously monitored signals. In this method, the condition monitoring data are first classified by exploiting the comprehensive evaluation technique, and then the feature data are used to train the corresponding diagnosis models, which themselves represent the different stages of system degradation. Due to the variant behavior of the ECLSS in the space environment, variational approximation-based learning is designed in the diagnostics procedure to estimate the parameter distribution of the trained models rather than the parameters themselves. By exploiting the constructed trained models, the current ECLSS health stage and remaining useful life (RUL) can be identified. A numerical stimulation is provided to demonstrate the performance of the proposed integrated algorithm.

Keywords Integrated system health management · Environmental control and life support system · Diagnostics · Prognostics

37.1 Introduction

Manned space flight allows for the exploration of the universe and is, by its very nature, complicated and innovative [14]. The functions of the earth's natural life support system such as the provision of air, water, and other conditions must be

F. Li (✉) · Y. Wang
Uncertainty Decision-Making Laboratory,Sichuan University,
Chengdu 610064, People's Republic of China
e-mail: lifanscu@sina.com

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performed by artificial means in manned spacecraft to guarantee that people can live and work in space. To meet this need, the environmental control and life support system (ECLSS) plays an important role in the development of future space shuttles to provide the crew with a comfortable environment in which to live [16]. ECLSS are critical subsystems in manned spacecraft as they are an indispensable safeguard for life in the harsh environmental conditions of space and on lunar and planetary surfaces [8].

Health management, which can guarantee the reliability of the system by evaluating its life-cycle conditions, determining the advent of failure, and mitigating system risks, has been viewed as having the role of an autonomic safeguard, and is also vital to complex systems such as the ECLSS [5, 12]. However, health management for ECLSS is a complex task, due to the complex system structures and the large amount of devices and interfaces in the ECLSS subsystems, both of which may cause complicated failure mechanisms. The complexity of the ECLSS can be attributed to the highly nonlinear behavior of the individual subsystems, the effect of which is further magnified by the number of interacting subsystems, and the fact that these systems have to operate with limited resources in unpredictable environments. In the ISHM for the ECLSS, the health stages for the system environment need to be comprehensively evaluated by exploiting the monitored data from different subsystems. Then, diagnostics are conducted to identify the current health condition and the extent of the degradation, and prognostics are then needed to predict the remaining useful life (RUL) and the associated confidence bounds for the system within the limited resources in space. Hence, an ISHM, with its efficient diagnostic and prognostic capability, has become a very important design requirement as a result of the need to provide the ECLSS in spacecraft with system level health management.

This paper deals with the integrated assessment, diagnostics and prognostics of a designed ISHM framework for an ECLSS. Previous research has discussed the key techniques, including data preprocessing, health assessment, diagnostics and prognostics respectively for ISHM, but the integrated capability in the complex system has not been well implemented which just focused on the conceptual framework design [4]. In this paper, integrated diagnostics and prognostics are presented for the ISHM of an ECLSS, by using data-based learning. In the proposed diagnostic and prognostic method, the diagnostics and prognostics can be performed in two main phases; the learning phase and the exploitation phase. During the learning phase, the monitored data with a known health condition are used in the trained diagnostic models to represent the system's health stages. The trained models are based on a mixture of Gaussian Hidden Markov Model (MoG-HMM), which allows for continuous observations through the taking in of input. By exploiting proposed learning algorithm, the parameter distributions of the MoG-HMM, rather than the fixed parameters, are estimated, which better represents the degradation of the complicated ECLSS in a complex environment. In the exploitation phase, when the monitored feature data are obtained, the current health stages of the ECLSS are determined by exploiting the statistical properties of the trained models. Based on the current diagnostics results, furthermore, the RUL and associated confidence bounds are estimated.

The rest of this paper is organized as follows: Sect. 37.2 first describes the ISHM scheme for the ECLSS, where the key to the ISHM implementation is presented. Then the integrated diagnostics model for ISHM is given in Sect. 37.3. Section 37.4 is dedicated to the proposed diagnostic and prognostic method. Numerical examples are illustrated to demonstrate the performance of the proposed algorithm in Sect. 37.5. Section 37.6 gives some conclusions.

37.2 Problem Statement

In general, the main functional subsystems of the ECLSS used in aeronautic and aerospace applications include a unified form: atmosphere control and supply (ACS), atmosphere revitalization (AR), temperature and humidity control (THC), water recovery and management (WRM), waste management (WM), fire detection and suppression (FDS), and spacesuits [9]. The ACS provides the cabin with sufficient oxygen and nitrogen, adjusting pressure immediately. The objective of the AR is to maintain the trace harmful gases in the crew's cabin within safe bounds. The THC ensures an equal distribution of temperature, humidity and gas around the astronauts. The WRM and WM deal with liquid and solid waste, respectively. The FDS monitors any exceptional smoke and fire situations to trigger a timely alarm. The spacesuit is a relatively independent subsystem which works as an emergency backup for the manned spacecrafts ECLSS. Depending on the duration and distance from earth of a mission, the ECLSS varies greatly in complexity [3, 13]. However, one of the key elements of the ECLSS, the ISHM for ECLSS, can have a direct bearing on crew safety and mission success and must be pursued with a careful and systemic consideration of the monitoring capability, safety margins, maintenance, and sustainment requirements. Therefore, ISHM-based state evaluation, diagnostics and prognostics have become necessary for the ECLSS in providing effective health management under an uncertain environment [6]. A feasible ISHM framework which considers integrated assessment, diagnostics and prognostics is proposed to improve the ECLSS health management at the system level. Figure 37.1 shows the ECLSS ISHM conceptual framework.

As can be seen in Fig. 37.1, data from the functional ECLSS subsystems are first monitored in situ, and then the data are pre-processed to extract feature parameters. For some health state factors it is difficult to give an accurate quantitative description and therefore expert knowledge and historical data are needed. Diagnostics and prognostics are then conducted used the health assessed information. In the ISHM conceptual framework, these processes determine the system's current state of health, diagnose and identify malfunctions, and estimate the advent of failure by providing a distribution of the RUL, and the current level of deviation or degradation [15]. The main purpose for the diagnostics and prognostics is to recognize the system's actual state and estimate the remaining time before failure. Based on that, the decisions for safeguarding and maintenance can be determined.

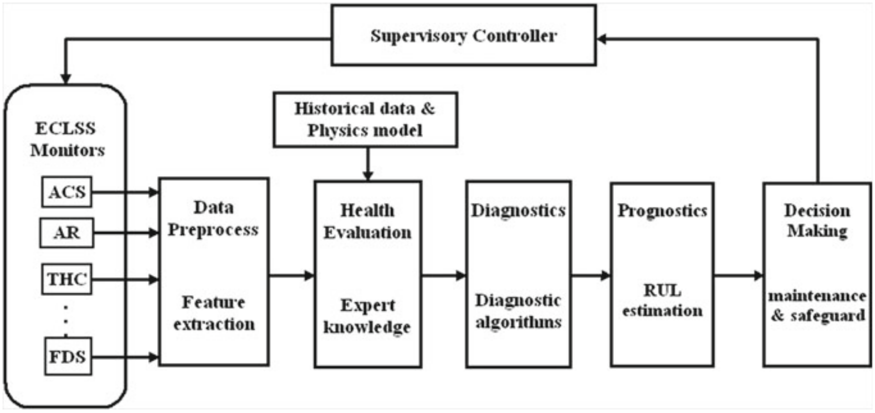

Fig. 37.1 ISHM conceptual framework for ECLSS

37.3 ISHM-Based Diagnostics Model

From the ECLSS ISHM framework, the diagnostics and prognostics are vital, but for an integrated implementation, the feature information needs to be used. For a complex system with limited resources, a degrading of the system, which cannot directly observed, may result from the transition of some different stages. The integrated ECLSS diagnostics and prognostics needs to make full use of the feature data from the monitoring sensors to build the behavioral models of the system states through a learning process.

Consider the characteristics of the whole system, the ECLSS health states are difficult to observe directly, as the only information that can be obtained is the monitored data from the subsystems. Usually, an HMM represents stochastic sequences as Markov chains, where the states are not directly observed, but the output depends on the states which are visible. Thus, let the Markov chains state sequence be $\{s_t\}_{t=1}^{T}$, i.e., $P(s_t|s_{t-1}, \cdots, s_1) = P(s_t|s_{t-1})$, $\forall t$, and the associated observation sequence be $Y = \{y\}_{t=1}^{T}$, supposed that $s_t \in \{1, 2, \cdots, N\}$, $y_t \in \{1, 2, \cdots, M\}$, $\forall t$, then the discrete HMM is completely defined by the following parameters:

1. The initial state distribution: $\pi = [\pi_i]$, where $\pi_i = P(s_1 = i)$, $1 \leq i \leq N$.
2. The state transition probability distribution: $A = [a_{ij}]$, where $a_{ij} = P(s_t = j|s_{t-1} = i)$, $1 \leq i, j \leq N$.
3. The observation probability distribution: $B = [b_i(k)]$, where $b_i(k) = P(y_t = k|s_t = i)$, $1 \leq i \leq N$, $1 \leq k \leq M$.

It can be seen that the model parameters for the HMM are π, A, B. The discrete HMM model considers the observations as discrete symbols and uses discrete probability densities to model the transition and the observation probabilities. However, the observations from the condition monitoring are typically continuous variant signals in practice [7, 10]. In order to overcome this limitation, the MoG-HMM can be used in which the distribution of the observations are viewed as a combination of a finite number of mixtures, i.e., $b_j(y_t) = \sum_{k=1}^{K} c_{jk} N(y_t; \mu_{jk}, \Sigma_{jk})$. In the Mixed Gaussian observations, let $z_t = k$ represent the k density at t, then the corresponding weight is $c_{jk} = P(z_t = k|s_t = j)$. By assuming a mixture of Gaussian rather than using just a Gaussian distribution, the observations can be identified with differing covariance structures. The complete parameter set of the MoG-HMM can be given by the compact notation $\theta = (\pi, A, B, C, \mu, \Sigma)$, where, $(\mu, \Sigma) = (\{\mu_{jk}\}, \{\Sigma_{jk}\})$.

The parameters of the models are important, as they can determine the MoG-HMMs. For the diagnostics learning process, the goal is to recognize the different ECLSS health stages by exploiting the trained models. Different trained models learn from different groups of monitored data, which represent the different health stages of the system. Therefore, the ECLSS diagnostics needs to develop the diagnosis models from the monitored data from varying health conditions, and so it is essential to learn the parameters of the models which represent the characteristics of their corresponding diagnosis model. However, because the ECLSS is under a complex space environment, the fixed parameters cannot represent the degradation when the system under conditions varies greatly, so there should be uncertain parameters with some distribution. In other words, the parameters of the trained model have an unknown distribution:

$$p(\theta) = p(\pi)p(A)p(C)p(\mu)p(\Lambda), \tag{37.1}$$

where $\Lambda = \Sigma^{-1}$, consider the parameters being independent. With the diagnostics model's parameter distribution, the extracted features information from the conditional monitoring histories are transformed into different MoG-HMMs associated to the ECLSS health stages. After that, when the current monitored data is obtained, the identification or exploitation can be conducted by comparing the observations likelihood under different trained models. According to the highest likelihood for the observations, the ECLSS current health stages can be identified.

37.4 Integrated Diagnostics and Prognostics

In order to implement the integrated diagnostics and prognostics for ECLSS in the space environment, the learning phase and exploitation phase need to exploit the parameter distributions of the diagnosis models. In this situation, the only solution is to estimate the distributions of those parameters using the Bayesian approach.

1. Variational Bayesian Method

The classical Bayesian inference is to estimate the conditional probability density of the unknown parameters θ under the condition of given observations Y. It is assumed that the density of observations Y with respect to the parameters θ, i.e., $p(Y|\theta)$, called the conditional likelihood function, can be known. The estimation result of the conditional probability density function $p(Y|\theta)$ with respect to a given observation Y, which is called the posterior distribution of θ, can be yielded as follows by using the Bayesian Theorem.

$$p(\theta|Y) = \frac{p(Y|\theta)p(\theta)}{\int p(Y|\theta)p(\theta)d\theta}\ . \tag{37.2}$$

Here $p(\theta)$ is the prior distribution of θ. Taking the Bayesian framework, the prior distributions of those parameters are assumed, then the posterior density of the parameters can be obtained by exploiting the observations likelihood.

From the above formula, the difficulty is that the analytical solution to calculate the integral of Eq. (37.2) is generally difficult. Several methods, such as the Monte Carlo method and sampling methods [11], are available but these require significant computational effort. Thus, the variational approximation method is used here to approximate the analytical solution of Eq. (37.1). In the diagnostics models from our learning phase, there are two unknown parameters: the model parameter θ and the hidden variable $\mathbf{x}$. Denoting the true posterior distribution of those parameters as $p(\mathbf{x}, \theta|\mathbf{y})$, and the approximated density as $q(\mathbf{x}, \theta)$, the approximation principle is given as follows.

From the observation log-likelihood $\log p(\mathbf{y})$, it can be expressed by:

$$\log p(\mathbf{y}) = \int \mathbf{dxd}\theta\mathbf{q}(\mathbf{x}, \theta)\log\frac{\mathbf{p}(\mathbf{x}, \mathbf{y}, \theta)}{\mathbf{p}(\mathbf{x},\ \mathbf{theta}|\mathbf{y})} = \mathbf{KL}(\mathbf{q}(\mathbf{x}, \theta)\|\mathbf{p}(\mathbf{x}, \theta|\mathbf{y})) + \mathbf{F}(\mathbf{q}(\mathbf{x}, \theta)), \tag{37.3}$$

where, $F(q(\mathbf{x}, \theta))$ can be written as:

$$F(q(\mathbf{x}, \theta)) = \int \mathbf{dxd}\theta\mathbf{q}(\mathbf{x}, \theta)\log\frac{\mathbf{p}(\mathbf{x}, \mathbf{y}, \theta)}{\mathbf{q}(\mathbf{x}, \theta)}$$

and it is actually the function of $q(\mathbf{x}, \theta)$.

From Eq. (37.3), the Kullback-Leibler (KL) divergence describing the distance between the true posterior density $p(\mathbf{x}, \theta|\mathbf{y})$ and its approximation $q(\mathbf{x}, \theta)$ is non-negative, and equal to zero if and only if the two densities are the same. Further, the left side of Eq. (37.3) does not depend on the estimated density. This means that minimizing the KL divergence is equivalent to maximizing $F(q(\mathbf{x}, \theta))$ by selecting the function q. Consequently, a distribution $q(\mathbf{x}, \theta)$ maximizing $F(q(\mathbf{x}, \theta))$ can be viewed as the best approximation of the true posterior distribution. Suppose that the model parameters are independent of the hidden variables in the approximation distribution, thus, its density can be written as $q(\mathbf{x}, \theta) = \mathbf{q}(\mathbf{x})\mathbf{q}(\theta)$. Then, the functional $F(q(\mathbf{x}, \theta))$ can be given as:

$$F(q(\mathbf{x}, \theta)) = \int \mathbf{dxd}\theta\mathbf{q}(\mathbf{x})\mathbf{q}(\theta)\log\frac{\mathbf{p}(\mathbf{x}, \mathbf{y}|\theta)}{\mathbf{q}(\mathbf{x})} + \int \mathbf{d}\theta\mathbf{q}(\theta)\log\frac{\mathbf{p}(\theta)}{\mathbf{q}(\theta)}. \tag{37.4}$$

In order to maximize the functional $F(q(\mathbf{x}, \theta))$ with the constraint $\int q(\mathbf{x}, \theta)$ $\mathbf{dxd}\theta = \mathbf{1}$. In fact, let the first term on the right side in Eq. (37.4) be $F(q(\mathbf{x}))$, then the maximization of the functional $F(q(\mathbf{x}, \theta))$ needs to maximize $F(q(\mathbf{x}))$, since $F(q(\mathbf{x})) = -\mathrm{KL}(\mathbf{q}(\mathbf{x}) \| \mathbf{Q}(\mathbf{x}))$, where $Q(\mathbf{x})$ can be approximated by $\exp[\langle \log p$ $(\mathbf{x}, \mathbf{y}|\theta) \rangle_{q(\theta)}]$ and the notation $\langle \cdot \rangle_{q(\cdot)}$ is represented as the expectation with density $q(\cdot)$. Therefore, solving the maximization $F(q(\mathbf{x}))$ can yield:

$$q^*(\mathbf{x}) = \mathbf{Q}(\mathbf{x}) \propto \exp[\langle \log \mathbf{p}(\mathbf{x}, \mathbf{y}|\theta) \rangle_{\mathbf{q}(\theta)}], \quad (37.5)$$

in the above notation $\propto$ refers to the achievement of equality with a normalizing constant. Similarly, consider that the model parameters θ can be decomposed by independent components. Accordingly, its density can be expressed by $q(\theta) = \prod_l q(\theta_l)$, so the variational posterior distribution of θ_l can be estimated as follows: $q^*(\theta_l) = Q(\theta_l) \propto p(\theta_l) \exp[\langle \log p(\mathbf{x}, \mathbf{y}|\theta) \rangle_{\mathbf{q}(\mathbf{x})\mathbf{q}(\theta_{-\mathbf{l}})}]$, where the $\theta_{-l} = \{\theta_1, \cdots, \theta_{l-1}, \theta_{l+1}, \cdots, \theta_N\}$. It can be seen that the above solution procedure can be computed iteratively until it converges. Actually, the above iteration procedure can be viewed as a special case of the expectation maximization (EM) algorithm, whereas the iterations terminate until the functional $F(q(\mathbf{x}, \theta))$ is converged.

2. Proposed Diagnostics and Prognostics Algorithm

In this section, the integrated ECLSS diagnostics and prognostics is presented based on the variational approximation. First of all, the prior distribution of the models parameters needs to be considered from the variational approximation scheme. Considered analytically intractable and with Bayesian properties, the conjugate prior is assumed which can be expressed as:

$$p(\pi) = \mathrm{Dir}(\pi; u^{\pi}), \quad p(A) = \prod_{i=1}^{N} \mathrm{Dir}(a_i; u_i^A), \quad p(C) = \prod_{j=1}^{N} \mathrm{Dir}(c_j; u_j^C),$$
$$p(\mu) = \prod_{k=1}^{K} \prod_{j=1}^{N} \mathscr{N}(\mu_{jk}; d_{jk}, D_{jk}^{-1}), \quad p(\Lambda) = \prod_{k=1}^{K} \prod_{j=1}^{N} \mathscr{W}(\Lambda_{jk}; v_{jk}, V_{jk}),$$

where, $\mathrm{Dir}(\cdot)$, $\mathscr{N}(\cdot)$, $\mathscr{W}(\cdot)$ are described as the DirichletGaussian and Wishart distributions respectively.

From the variational approximation principle, the conditional distribution of the observations with the given model's parameters and the hidden variables needs to be exploited to drive the posterior of the model's hidden variables. The hidden variables in our MoG-HMM-based trained models are the sequence s_t and the mixture component variables z_t which are shown as $\mathbf{x}$ in Eq. (37.2). To express the conditional distribution of the observations for the iteration procedure, it is assumed that the posteriors for the parameters are available from the previous iteration. For simplicity and clarity of presentation, the superscript "′" is use to describe the posterior of the model's parameter distributions obtained in the previous iteration, a tilde indicates an updated posterior for the parameter distributions, or a density of the condition observations and hidden variables. From Eq. (37.5), the likelihood of each observation y_t with a given hidden sequence and mixture component variables can be written as:

$$\begin{aligned}\widetilde{p}(y_t|s_t=j,z_t=k) &\propto \exp[\langle \log \mathcal{N}(y_t;\mu_{jk},\Lambda_{jk}^{-1})\rangle_{q'(\mu_{jk})q'(\Lambda_{jk})}] \\ &= \exp\left[-\frac{n}{2}\log 2\pi + \frac{1}{2}\langle \log|\Lambda_{jk}|\rangle_{q'(\Lambda_{jk})} - \frac{\widetilde{v}'_{jk}}{2}(y_t-\widetilde{d}'_{jk})^T \widetilde{V}'_{jk}(y_t-\widetilde{d}'_{jk})\right],\end{aligned} \tag{37.6}$$

using the expressions, the follow densities can be computed: $\widetilde{p}(y_t|s_t) = \sum_{z_t} \widetilde{p}(y_t,z_t|s_t) = \sum_k \widetilde{c}_{jk}\widetilde{p}(y_t|s_t=j,z_t=k)$, notice that the $\widetilde{p}(z_t|s_t)$, corresponds to the parameters $\widetilde{C} = [\widetilde{c}_{jk}] \propto [\exp(\langle \log c_{jk}\rangle_{q'(c_{jk})})]$. In the variational approximation, the joint posterior densities of the hidden variables and the posterior densities of the distribution parameters interact and can be approximated iteratively until convergence. To implement the procedure, the forward and backward recursions need to be noticed. Utilizing the Markov properties of the models, the recursive formula can be given respectively as follows:

$$\alpha(s_t) = \widetilde{p}(s_t|y_{1:t}) \propto \widetilde{p}(y_t|s_t)\sum_i \widetilde{a}_{ij}\alpha(s_{t-1}), \tag{37.7}$$

$$\beta(s_t) = \widetilde{p}(y_{t+1:T}|s_t) = \sum_j \widetilde{a}_{ij}\widetilde{p}(y_{t+1}|s_{t+1})\beta(s_{t+1}), \tag{37.8}$$

where, the updated parameters: $\widetilde{\pi} = [\widetilde{\pi}_i] \propto [\exp(\langle \log \pi_i\rangle_{q'(\pi_i)})]$, $\widetilde{A} = [\widetilde{a}_{ij}] \propto [\exp(\langle \log a_{ij}\rangle_{q'(a_{jk})})]$.

The initial conditions of Eqs. (37.7) and (37.8) are $\alpha(s_1) \propto \widetilde{p}(y_t|s_t)\widetilde{\pi}$, $\beta(s_T) = [1,\cdots,1]'$. The computing detail can be found in the appendices.

Using the above notations, the updated distribution of the health state at time, and the joint posterior for the two states in interval time can be yielded:

$$q^*(s_t) = \widetilde{p}(s_t|Y) = \frac{\widetilde{p}(s_t|y_{1:t})\widetilde{p}(y_{t+1:T}|s_t)}{\widetilde{p}(y_{t+1:T}|y_{1:t})} = \frac{\alpha(s_t)\beta(s_t)}{\sum_{s_t}\alpha(s_t)\beta(s_t)}, \tag{37.9}$$

$$q^*(s_{t-1},s_t) = \widetilde{p}(s_{t-1},s_t|Y) = \frac{\alpha(s_{t-1})\widetilde{p}(s_t|s_{t-1})\widetilde{p}(y_t|s_t)\beta(s_t)}{\sum_{s_t,s_{t-1}}\alpha(s_{t-1})\widetilde{p}(s_t|s_{t-1})\widetilde{p}(y_t|s_t)\beta(s_t)}, \tag{37.10}$$

similarly, the joint posterior for the two hidden variables is:

$$q^*(s_t,z_t) = \widetilde{p}(s_t,z_t|Y) = \frac{\widetilde{p}(y_t|s_t,z_t)\widetilde{p}(z_t|s_t)}{\widetilde{p}(y_t|s_t)}q^*(s_t). \tag{37.11}$$

The posterior distribution of the trained models parameters can be updated by exploiting the current densities of the hidden variables. Thus, for the different assumed priors of the MoG-HMM parameters, the following results can be achieved:

denote $q^*(s_t) = \tau_t = [\tau_{ti}]$, $q^*(s_{t-1}, s_t) = \eta_t = [\eta_{tij}]$, $q^*(s_t, z_t) = \omega_t = [\omega_{tjk}]$, then the Dirichlet posteriors for the initial distribution, the transition parameter, and the mixture components can be updated by:

$$q^*(\pi) = \mathrm{Dir}(\pi; \widetilde{u}^{\pi}), \quad q^*(A) = \prod_{i=1}^{J} \mathrm{Dir}(a_i; \widetilde{u}_i^{A}), \quad q^*(C) = \prod_{j=1}^{J} \mathrm{Dir}(c_j; \widetilde{u}_j^{C}),$$

where $\widetilde{u}_i^{\pi} = u_i^{\pi} + \tau_{1j}$, $\widetilde{u}_{ij}^{A} = u_{ij}^{A} + \sum_{t=2}^{T} \eta_{tij}$, $\widetilde{u}_{jk}^{C} = u_{jk}^{C} + \sum_{t=1}^{T} \omega_{tij}$.

For the Gaussian posteriors of the mixture component parameters, we have: $q^*(\mu_{jk}) = \mathscr{N}(\mu_{jk}; \widetilde{d}_{jk}, \widetilde{D}_{jk}^{-1})$, where, $\widetilde{D}_{jk} = D_{jk} + \widetilde{v}'_{jk} \widetilde{V}'_{jk} \sum_{t=1}^{T} \omega_{tjk}$, $\widetilde{d}_{jk} = \widetilde{D}_{jk}^{-1}(D_{jk} d_{jk} + \widetilde{v}'_{jk} \widetilde{V}'_{jk} \sum_{t=1}^{T} \omega_{tjk} y_t)$.

The Wishart posteriors for the parameter distribution matrices can be given by: $q^*(\Lambda_{jk}) = \mathscr{W}(\Lambda_{jk}; \widetilde{v}_{jk}, \widetilde{V}_{jk})$, where, $\widetilde{v}_{jk} = v_{jk} + \sum_{t=1}^{T} \omega_{tjk}$, $\widetilde{V}_{jk}^{-1} = V_{jk}^{-1} + \sum_{t=1}^{T} \omega_{tjk}(y_t - \widetilde{d}'_{jk})(y_t - \widetilde{d}'_{jk})^T + (\widetilde{D}'_{jk})^{-1} \sum_{t=1}^{T} \omega_{tjk}$. It can be seen that the posterior updating for the diagnosis model's parameters and the hidden state variables can be computed recursively. The termination condition can choose the variational free energy $F(q(\mathbf{x}, \theta))$ to converge or until the maximum number of iterations is reached.

After the above learning for the diagnosis models, the conditional observations representing different degradation stages are classified on the basis of the trained MoG-HMMs. Then, the identification of the ECLSS current health stages when the next observation is obtained need to exploit the observation likelihood to find the trained model that best fits with the current observations. Thus, the probability $P(y_{1:T}|\theta)$ under the different models parameters needs to be computed. For the trained models corresponding to the N health stages, let $\lambda_i^{(n)}(t) = P(y_{1:t}, s_t = i|\theta^{(n)})$ be the probability of the $y_{1:t}$ ending in state i under the trained model $\theta^{(n)}$, $n = 1, \cdots, N$, then the likelihood of the given observations $y_{1:T}$ can be written as: $\lambda_i^{(n)}(1) = \pi_i^{(n)} b_i^{(n)}(y_1)$, $\lambda_j^{(n)}(t+1) = [\sum_{i=1}^{N} \lambda_i^{(n)}(t) a_{ij}^{(n)}] b_j^{(n)}(y_{t+1})$, $P(y_{1:T}|\theta^{(n)}) = \sum_{i=1}^{N} \lambda_i^{(n)}(T)$.

For the integrated prognostics, the system RUL can be estimated using the diagnostics information. Taking into account the transition instant between the states, let D_i be defined as the duration of state i, then: $D_i \triangleq \sum_t E[I(s_t = i)] = \sum_t r_i(t)$.

From the posterior distribution of the state, the $D_i = \sum_t \tau_{ti}$. Given the Gaussian distribution assumption, the mean time duration μ_{D_i} and the standard deviation σ_{D_i} of the state can be estimated by:

$$\mu_{D_i} = \frac{1}{N} \sum_{t=1}^{N} (D_i)_t, \quad \sigma_{D_i} = \sqrt{\frac{1}{N} \sum_{t=1}^{N} [(D_i)_t - \mu_{D_i}]^2}.$$

Table 37.1 The number of training and testing data

Stages	S_0		S_1		S_2		S_3		S_4	
Learning	Training	Testing	Training	Testing	Training	Testing	Training	Testing	Training	Testing
Number	8	1	9	2	10	2	10	2	8	1

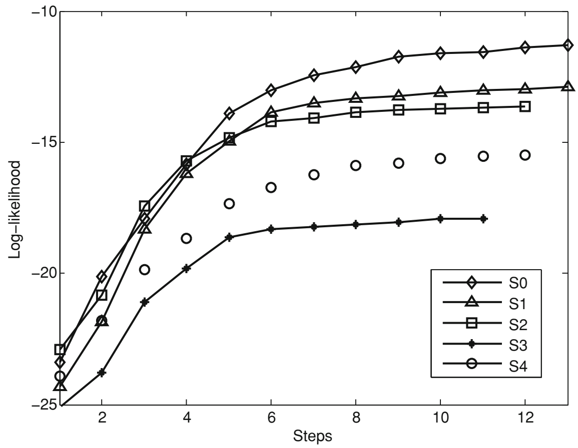

Fig. 37.2 The learning log-likelihood curve of different stages

37.5 Numerical Simulation

In this section, the integrated diagnostics and prognostics method presented previously was tested on a rich condition monitoring database taken from the test system containing different health stages simulated until failure. The diagnosis feature data was first classified through a health evaluation, then the different health stages which are most common in the ECLSS were identified and the prognostics results were determined using the diagnosis information for the new feature. The performance of the proposed variational approximation-based integrated diagnostics and prognostics was illustrated by a comparison with the existing methods based on the HMMs and HSMMs.

1. Diagnosis Models Training

On the basis of this evaluation information, the health stages represented by the monitored data which from the different subsystems were determined, so the corresponding feature data with known health conditions can be used for the MoG-HMMs training in the learning phase. In the two situations, the number of the training feature data and the test data under different situations are given in Table 37.1.

The log-likelihood through the training procedure in the proposed learning algorithm are given in Fig. 37.2.

Here, we compare the two existing methods with our method in which the first is the method based on the HMM in which the discrete parameters are learned using

Table 37.2 Diagnostics results based on three methods

Likelihood value	Test S_0	Test S_1	Test S_1	Test S_2	Test S_2	Test S_3	Test S_3	Test S_4
EM-HMM$_0$	−11.23	−inf	−inf	−inf	−inf	−inf	−inf	−inf
EM-HMM$_1$	−inf	−inf	−18.73	−inf	−inf	−inf	−inf	−inf
EM-HMM$_2$	−inf	−inf	−inf	−19.26	−12.21	−inf	−inf	−inf
EM-HMM$_3$	−inf	−inf	−inf	−inf	−inf	−21.93	−32.14	−inf
EM-HMM$_4$	−inf	−inf	−inf	−inf	−inf	−inf	−inf	−19.26
HSMM$_0$	−16.74	−32.65	−23.31	−17.78	−19.61	−28.67	−27.11	−17.64
HSMM$_1$	−21.41	−21.43	−17.36	−23.26	−29.14	−37.76	−32.73	−23.31
HSMM$_2$	−23.74	−38.21	−31.68	−14.87	−16.73	−43.71	−36.17	−34.18
HSMM$_3$	−27.35	−41.64	−38.97	−21.33	−31.12	−24.46	−23.57	−37.14
HSMM$_4$	−18.64	−35.38	−26.82	−19.23	−18.67	−32.65	−29.54	−13.72
MoG-HMM$_0$	−9.38	−17.63	−24.64	−17.14	−19.23	−23.16	−33.65	−19.34
MoG-HMM$_1$	−17.63	−16.45	−19.23	−21.76	−31.75	−36.77	−48.23	−23.47
MoG-HMM$_2$	−24.57	−32.28	−31.78	−11.68	−14.71	−34.84	−39.76	−21.68
MoG-HMM$_3$	−11.74	−43.67	−45.85	−28.44	−38.23	−17.65	−21.41	−31.63
MoG-HMM$_4$	−38.24	−21.34	−23.76	−16.28	−21.67	−21.36	−32.28	−14.76

Table 37.3 Mean and variance of RUL for different healthstates

Stages	S_0	S_1	S_2	S_3	S_4
RUL_{mean}	238.63	196.32	71.64	42.47	19.33
$RUL_{variance}$	1.65	1.24	1.87	2.41	1.56

the expectation maximization (EM) algorithm [1], and the second method was based on the Hidden Semi-Markov Models (HSMM) [2].

2. Diagnostics Results

The diagnostics results for the three different methods (EM-HMM, HSMM, MoG-HMM) are shown in Table 37.2. From Table 37.2, the log-likelihood values of the tested monitored observations under different trained models are yielded, thus, the system health stages are able to choose the diagnosis model with the maximum log-likelihood value. For the diagnostics results from situation1, the recognition rate based on the traditional HMM, which itself has been based on the EM algorithm is $7/8 = 87\,\%$, and the recognition rate based on the HSMM and the MoG-HMM with proposed variational approximation learning is $7/7 = 100\,\%$. Therefore, the new method is effective as a method based on HSMM, when the degradation models can be determined by fixed parameters.

Based on above diagnostics results, the statistical properties of the trained models representing four health stages can be obtained. The test data was generated randomly, thus the associated confidence value estimations can also be obtained. From these, the mean and variance of the duration in each state are also available using the prognostics algorithm. The results are given in Table 37.3.

37.6 Conclusion

An integrated diagnostics and prognostics for ECLSS in a manned-spacecraft has been presented in this paper. To implement the ECLSS health management at the system level, the proposed method makes full use of a health condition evaluation to diagnose the current health stages of the system, and predict the statistical properties of the RUL. In the proposed method, the feature data from different health stages are transformed to the corresponding MoG-HMMs, which take the feature as continuous observations. Different from the existing data-driven method based on parameter learning for the trained diagnosis models, the variational approximation-based technique is used to learn the distributions of the model parameters. Based on the diagnostics information of the trained models, the health stages are able to be identified when the next features are received, so the RUL and the associated confidence value estimations can also be obtained. Numerical examples demonstrated the effectiveness of the proposed integrated approach.

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References

1. Dempster AP, Laird NM, Rubin DB (1977) Maximum likelihood from incomplete data via the EM algorithm. J Roy Stat Soc Ser B (Methodol) 39:1–38
2. Dong M, He D (2007) A segmental hidden semi-Markov model (HSMM)-based diagnostics and prognostics framework and methodology. Mech Syst Signal Process 21(5):2248–2266
3. Feron P, Jacobs P et al (1997) Integrated CO_2 and humidity control by membrane gas absorption. Sixth Eur Symp Space Environ Control Syst 400:761–766
4. Figueroa F, Holland R et al (2006) Integrated system health management (ishm): systematic capability implementation. In: Proceedings of the 2006 IEEE sensors applications symposium, USA, pp 202–206
5. Glavaski S, Subramanian D et al (2007) A nonlinear hybrid life support system: dynamic modeling, control design, and safety verification. IEEE Trans Control Syst Technol 15(6):1003–1017
6. Hager P, Czupalla M, Walter U (2010) A dynamic human water and electrolyte balance model for verification and optimization of life support systems in space flight applications. Acta Astronaut 67(9):1003–1024
7. Li F, Zhou J, Wu D (2013) Optimal filtering for systems with finite-step autocorrelated noises and multiple packet dropouts. Aerosp Sci Technol 24(1):255–263
8. Marshall Space Flight Center (2002) International space station environmental control and life support system, USA, Report No. FS-2002-05-85-MSFC
9. National Aeronautics and Space Administration (2002) The framework of the environmental control and life support system
10. Rabiner LR (1989) A tutorial on hidden markov models and selected applications in speech recognition. Proc IEEE 77(2):257–286
11. Roberts SJ, Penny WD (2002) Variational bayes for generalized autoregressive models. IEEE Trans Signal Process 50(9):2245–2257

12. Tatara JD, Roman MC et al (1998) An overview of ISS ECLSS life testing at NASA, MSFC. Life Support Biosph Sci Int J Earth Space 5(1):13–21
13. Traweek MS, Tatara JD (1998) Overview of the environmental control and life support system (ECLSS) testing at MSFC. Life Support Biosph Sci Int J Earth Space 5(1):5–12
14. Woolford BJ (1986) Manned space flight. In: Proceedings of the Human Factors and Ergonomics Society annual meeting, vol 30. SAGE Publications, London, pp 354–357
15. Xu J, Li F, Xu L (2013) Distributed fusion parameters extraction for integrated system health management to space avionics. J Aerosp Inf Syst 10(9):430–443
16. Zongpeng Z (2009) The current situation of China manned aerospace technology and the direction for its further development. Acta Astronaut 65(3):308–311