Postprint: Equipment Health Diagnosis and Remaining Useful Life Prediction Based on an Improved Degradation Hidden Markov Model

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Abstract

To address the significant deviation of Hidden Markov Models (HMMs) from actual conditions in equipment health diagnosis, an improved Degradation-based Hidden Markov Model (DGHMM) centered on power-like relationship accelerated degradation is proposed. First, a degradation factor is introduced to characterize the equipment deterioration process. Compared with conventional exponential accelerated degradation, the proposed power-like relationship accelerated degradation can better describe the gradual performance decline during equipment service life as service age increases. Second, an improved genetic algorithm with relatively stronger global search capability is employed for parameter estimation instead of the conventional EM algorithm, overcoming the limitation of the EM algorithm' s tendency to fall into local optima. Meanwhile, to address the limitation that Hidden Markov Models must temporally follow an exponential distribution and cannot be directly applied to life prediction, a greedy approximation method based on approximation algorithms and the Viterbi algorithm is proposed. With the objective of seeking maximum probability remaining observations, this method dynamically searches for the maximum probability remaining state path to predict equipment remaining useful life (RUL). Finally, the proposed method is validated and evaluated using the hydraulic pump dataset from Caterpillar Inc. Results demonstrate that the equipment health diagnosis and remaining useful life prediction method based on the improved degradation-based Hidden Markov Model is more effective in characterizing equipment degradation and improving equipment state diagnosis accuracy, and is also feasible for remaining useful life prediction.

Full Text

Preamble

Equipment Health Diagnostics and Prognostics Method Based on Improved Degenerated HMM

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Abstract: To address the significant deviation between conventional Hidden Markov Models (HMM) and actual equipment health diagnosis, this paper proposes an improved Degenerated Hidden Markov Model (DGHMM) centered on quasi-power relation accelerated degradation. First, degradation factors are introduced to describe the equipment deterioration process. The proposed quasi-power relation accelerated degradation better captures the gradual performance decline with increasing service age compared to conventional exponential accelerated degradation. Second, an improved genetic algorithm with stronger global search capability replaces the conventional EM algorithm for parameter estimation, overcoming the limitation of EM' s tendency to fall into local optima. Meanwhile, to address the limitation that HMM cannot be directly used for life prediction due to its exponential distribution assumption, a greedy approximation method based on approximation algorithms and the Viterbi algorithm is proposed. This method dynamically seeks the maximum-probability remaining state path with the objective of maximizing the probability of remaining observations, thereby predicting equipment residual life. Finally, the proposed method is validated and evaluated using hydraulic pump datasets from Caterpillar Inc. Results demonstrate that the equipment health diagnosis and remaining useful life (RUL) prediction method based on the improved degenerated HMM is more effective in depicting equipment degradation and achieving higher diagnostic accuracy, while also proving feasible for RUL prediction.

Keywords: hidden Markov model; equipment degradation; health diagnostics; residual useful lifetime; genetic algorithm; approximation algorithm

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0 Introduction

As a statistical approach, the Hidden Markov Model (HMM) describes the relationship between a system' s external manifestations and its latent states from a probabilistic perspective, capturing both the randomness and underlying structure of complex systems. This makes it suitable for modeling complex systems and has achieved success not only in speech recognition and word segmentation [?, ?] but also in pattern recognition and health diagnostics.

Carey et al. [?] first successfully applied HMM to fault diagnosis by analyzing vibration signals from mechanical equipment. Wang et al. [?] established a model incorporating coupled discrete time-varying delays and coupled distributed time-varying delays, constraining uncertain terms through effective techniques and validating the method through numerical simulation. Ma et al. [?] elaborated on the inherent unreasonableness of HMM' s mandatory exponential distribution assumption in the time domain, which prevents direct application to remaining life prediction. Overall, current HMM research remains limited to equipment health diagnosis due to these inherent constraints.

To overcome HMM limitations, researchers proposed the Hidden Semi-Markov Model (HSMM). Dong et al. [?] utilized HSMM state sojourn times for equipment health diagnosis and RUL prediction. Liu [?] employed K-means and cross-validation algorithms to determine power grid degradation stages and used HSMM for grid diagnosis and life prediction. Additionally, for multi-sensor and multi-input models, scholars have proposed various methods to integrate sensor signals, enabling more accurate system state identification and life prediction [?, ?]. These studies share a common characteristic: HSMM inherently relies on prior distributions, inevitably introducing a degree of subjectivity.

As research on HMM and HSMM deepened, investigators discovered that Markov-type models still exhibit significant discrepancies in state identification compared to reality. To develop models that better reflect actual equipment conditions, equipment degradation theory emerged. Chen et al. [?] noted that traditional models assume fixed state transition probabilities, whereas in reality, equipment deterioration accumulates with operating time, necessitating changes in state transitions. Peng [?] designed three types of degradation factors for HSMM, re-deriving algorithms and re-estimating parameters. He et al. [?] applied these three degradation factors to HSMM, built a piston pump experimental platform, and validated degradation effectiveness through case studies. Most existing degradation research focuses on applying degradation to models with assumed prior distributions, leaving a gap in studies optimizing the degradation factors themselves.

Maximum likelihood estimation serves as a common parameter estimation method, seeking parameters that maximize the likelihood of experimental data. Correspondingly, the EM algorithm is widely used for parameter estimation due to its relative simplicity and efficiency, yet it suffers from the drawback of easily falling into local optima. To address this limitation, increasing numbers of researchers have applied intelligent algorithms to parameter estimation. Yuan et al. [?] used an improved PSO algorithm to modify the Baum-Welch algorithm, obtaining more accurate parameters. Yu et al. [?] applied genetic algorithms to parameter estimation in grey models, with numerical results showing significantly improved prediction accuracy. Krause et al. [?] employed a genetic algorithm-based function approximator to estimate induction motor parameters, achieving better results than alternative methods. Zhang et al. [?] used artificial immune algorithms to optimize HMM, obtaining the most distinguishable initial observation matrix. Zhang et al. [?] utilized adaptive genetic particle swarm algorithms to optimize coupled HMM (CHMM), yielding more accurate results than traditional HSMM. As an intelligent optimization algorithm with strong global search capabilities, genetic algorithms have not yet been applied to Markov-type models, presenting an area for exploration.

Building upon these issues, this paper first introduces degradation factors to model equipment deterioration, obtaining a description of the degradation process, and proposes a DGHMM centered on quasi-power relation accelerated degradation. Compared to conventional exponential accelerated degradation, this more accurately describes the process of equipment performance gradually accelerating downward with increasing service age. An improved genetic algorithm replaces the conventional EM algorithm for parameter estimation across the entire model. Additionally, to address HMM's limitation in direct life prediction, a greedy approximation method based on approximation algorithms and the Viterbi algorithm is proposed, using changes in state transition probability matrices during equipment degradation to predict remaining life. Finally, the model is validated and evaluated using hydraulic pump datasets from Caterpillar Inc., with results demonstrating the feasibility and effectiveness of the proposed method.

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1 HMM Model

The HMM formulation can be described as follows:

a) N: Number of states, with the state set denoted as $\{S_1, S_2, \dots, S_N\}$. At any time t, the state is $s_t \in \{s_1, s_2, \dots, s_N\}$.

b) M: Number of observations, with the observation set denoted as $\{\theta_1, \theta_2, \dots, \theta_M\}$. The observation generated by state s_t at time t is $o_t \in \{\theta_1, \theta_2, \dots, \theta_M\}$.

c) π: Initial state probability distribution, $\pi = \{\pi_1, \pi_2, \dots, \pi_N\}$, where $\sum_{i=1}^{N} \pi_i = 1$. The initial probability vector represents the probability of the model being in each state at time $t = 1$.

d) A: State transition matrix. A is an $N \times N$ matrix $[a_{ij}]_{N\times N}$, where a_{ij} is the probability of transitioning from state S_i to state S_j, i.e., $a_{ij} = P(S_j^{t+1} | S_i^t)$. The assumption that these probabilities remain constant over time limits HMM's practical modeling capability. To address this, time-varying HMM has been proposed.

Typical equipment degradation patterns can be illustrated in [Figure 1: see original paper]. The entire degradation process comprises three stages: A, B, and C. Stage A represents stable degradation, where equipment performance indices remain essentially stable. Stage B represents uniform degradation, where performance indices change uniformly. Stage C represents accelerated degradation, where performance declines at an accelerating rate as service life progresses, with health status deteriorating rapidly until reaching complete failure threshold.

In most existing studies, degradation factors for these three stages are typically defined as constant, linear functions, and exponential functions, respectively. For the exponential degradation stage, the state transition probability between adjacent time periods t and $t+1$ is generally expressed as $\phi_i(t) = \phi_0 \cdot \exp(\alpha_i \cdot t)$, where α_i is a parameter to be estimated. Based on Peng' s definition of degradation factors [**?**], equipment accelerated degradation is a recursive process. For discrete-time state transitions, the state degradation relationship is defined as $f(X) = f(X-1) \cdot \phi_i(t)$. After X recursions, the internal transition probability value is $f(X)$, and the degradation function should satisfy:

$$f(0) = f_{\text{end}} \quad (1)$$

$$f(X) - 2f(X-1) + f(X-2) > 0 \quad (2)$$

Equation (1) represents the internal transition probability at the end of uniform degradation, i.e., the initial value of recursion. Equation (2) captures the acceleration concept during accelerated degradation: the closer to end-of-life, the faster the probability of remaining in the current state declines.

For the accelerated degradation relationship definition, based on analysis of exponential recursive structures, a new quasi-power relation accelerated degradation is proposed:

$$\phi_i(t) = \phi_0 \cdot \left(1 - \frac{\alpha_i}{t}\right) \quad (3)$$

where α_i is a parameter to be estimated from historical data. Since state transition probabilities must be less than 1 and ϕ_0 equals 1, boundary values must be subtracted to obtain adapted state transition probabilities.

Comparing exponential and quasi-power relations with appropriate parameters that satisfy recursive accelerated degradation requirements reveals that under reasonable parameters, both exhibit similar recursive accelerated degradation effects, as shown in [Figure 2: see original paper]. Subplots (a) and (b) illustrate exponential and quasi-power degradation diagrams under reasonable parameters for the accelerated degradation process, respectively. The thick solid lines represent continuous function graphs, thick dashed lines represent inverse functions, and dotted lines represent state transition probabilities during recursion. The results show functional similarity between the two relations. Subplots (c) and (d) depict the degradation processes under current example parameters, with solid lines representing single-time-point state probabilities and dashed lines representing partial degradation processes. The quasi-power relation demonstrates superior performance in expressing accelerated degradation compared to the exponential relation.

2.1 Degradation Factor Design

Conventional HMM assumes constant state transition probabilities throughout the equipment lifecycle. However, equipment operation is an irreversible degradation process without manual intervention—equipment states can only remain in the current state or degrade to worse states. Therefore, the initial state transition probability matrix A can be described as:

$$A = \begin{pmatrix} a_{11} & 1-a_{11} & 0 & \cdots & 0 \\ 0 & a_{22} & 1-a_{22} & \cdots & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & 0 & \cdots & 1 \end{pmatrix}$$

Combining the three degradation recursion formulas with the transition probability matrix yields state transition probability matrices after experiencing t time units in different degradation stages:

a) **Stable degradation stage**: The probability change of equipment remaining in the current state between adjacent time points t and $t+1$ is constant, i.e., $\phi_1(t) = \phi_1$ and $0 \leq \phi_1 \leq 1$. As the probability of remaining in the current state decreases, the probability of transitioning to other states increases proportionally. The state transition probability at the next moment in stable degradation is:

$$a_{ii}^{(t+1)} = a_{ii}^{(t)} - \phi_1 \cdot a_{ii}^{(t)} \quad (4)$$

$$a_{ij}^{(t+1)} = a_{ij}^{(t)} + \phi_1 \cdot a_{ii}^{(t)} \cdot \frac{a_{ij}^{(t)}}{\sum_{j \neq i} a_{ij}^{(t)}} \quad (5)$$

The state transition probability at any time point during stable degradation can be derived recursively from the initial moment:

$$a_{ii}^{(t)} = a_{ii}^{(0)} \cdot (1-\phi_1)^t \quad (6)$$

b) **Uniform degradation stage**: The probability change between adjacent time periods t and $t+1$ is a linear function of time, i.e., $\phi_2(t) = \phi_2 \cdot t$ and $0 \leq \phi_2 \leq 1$. The decreased value is similarly allocated:

$$a_{ii}^{(t+1)} = a_{ii}^{(t)} - \phi_2 \cdot t \cdot a_{ii}^{(t)} \quad (7)$$

Defining the time point when stable degradation ends as t_e, the state transition probability at any time point during uniform degradation can be described as:

$$a_{ii}^{(t)} = a_{ii}^{(t_e)} \cdot \prod_{k=t_e+1}^{t} (1 - \phi_2 \cdot k) \quad (8)$$

Equation (8) represents the state transition probability matrix after t time units from initial time to t_e when the system is in uniform degradation.

c) **Quasi-power accelerated degradation stage**: For the proposed quasi-power accelerated degradation, the probability change of equipment remaining in the current state between adjacent time periods is $\phi_3(t) = \phi_2 \cdot t^{-\alpha_i}$ with $0 \leq \phi_2 \leq 1$ and $\alpha_i > 0$. The decreased value is allocated to a_{ij}:

$$a_{ii}^{(t+1)} = a_{ii}^{(t)} - \phi_2 \cdot t^{-\alpha_i} \cdot a_{ii}^{(t)} \quad (9)$$

Defining the time point when uniform degradation ends as t_{e2}, and letting A_{e1} denote the state transition probability matrix at the end of uniform degradation, the state transition probability matrix after experiencing t time units in quasi-power accelerated degradation is:

$$a_{ii}^{(t)} = a_{ii}^{(e1)} \cdot \prod_{k=t_{e2}+1}^{t} (1 - \phi_2 \cdot k^{-\alpha_i}) \quad (10)$$

Due to the special recursive form of the quasi-power relation, we introduce the recursive relation symbol $f_X(x)$, where X represents recursion count and x represents initial recursion probability value. The state transition probability at any time point in this accelerated degradation stage is:

$$a_{ii}^{(t)} = f_{t-t_{e2}}\left(a_{ii}^{(e2)}\right) \quad (11)$$

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3 Parameter Estimation Based on Improved Genetic Algorithm

To address the limitation of the EM algorithm's tendency to fall into local optima in maximum likelihood estimation, this paper employs a genetic algorithm with stronger global search capability for DGHMM parameter estimation. The log-likelihood function is established as:

$$L(\lambda, \phi_1, \phi_2, \phi_3, \theta) = \log(\Pr(O_{1:T}|\lambda, \phi_1, \phi_2, \phi_3, \theta)) \quad (12)$$

Each parameter set used for iteration calculates a likelihood value serving as the fitness of an individual solution. The optimal individual in each population iteration can be represented as $\arg\max \log(\Pr(O_{1:T}|\lambda, \phi_1, \phi_2, \phi_3, \theta))$.

3.1 Improved Encoding

This paper adopts a hybrid encoding strategy. For the transition probability matrix $A_{N\times N}$, the matrix is first flattened. Due to the characteristics of transition probability matrices, only $N^2 - N$ values are actually meaningful. Considering that probability values are less than 1 and mostly multi-digit decimals, decimal floating-point encoding with three decimal places is used. The flattened transition probability matrix, after removing zeros and ones, becomes the transition probability chromosome in a parameter set. The flattened observation probability matrix becomes the observation chromosome. The initial state distribution π is similarly represented using an N-point decimal floating-point encoding chromosome (retaining three decimal places).

For the degradation factor λ, considering the model' s high sensitivity to this parameter, binary integer encoding with five decimal places is adopted. An 18-bit binary integer chromosome represents the absolute value of λ, where the first bit indicates the integer part and does not participate in binary-decimal conversion. The remaining 17 bits are scaled down by 10^5 during decoding, then added to the first bit value to obtain the decoded parameter. The encoded chromosomes for each variable are shown in [Figure 3: see original paper].

In the three-parameter encoding, one chromosome locus represents one probability value in the matrix, with each locus comprising four parts. The gray portion represents the integer part of a matrix value, while white portions represent the tenths, hundredths, and thousandths digits. Throughout the improved genetic algorithm process, parameters within a single parameter set always participate in calculations simultaneously, with one parameter set representing a complete solution.

3.2 Improved Crossover

Corresponding to the improved hybrid encoding strategy, crossover and mutation operations are also enhanced. Two different crossover methods are designed for the three parameters with similar encoding schemes.

Crossover Method 1 exchanges the thousands/hundreds and tens/integer digits at the same locus between two random chromosomes, followed by adaptive normalization of the resulting new chromosomes.

Crossover Method 2 exchanges entire segments between two random chromosomes at the same locus, followed by adaptive normalization.

Since chromosomes are flattened matrix products and matrix row sums equal 1, adaptive normalization must satisfy certain constraints. The specific adaptive normalization rules are shown in , with chromosome loci counted from 1.

TABLE:1 Adaptive Normalization Rule

Chromosome Category	Locus Range	Normalization Constraint
Transition chromosome ($N \times N$)	1 to N	$\sum_{j=1}^{N} a_{ij} = 1$
	$N+1$ to $2N-1$	$\sum_{j=2}^{N} a_{ij} = 1 - a_{i1}$
	$(N-1)M+1$ to NM	$\sum_{j=1}^{M} b_{ij} = 1$
Initial chromosome (N)	1 to N	$\sum_{i=1}^{N} \pi_i = 1$

Mutation operations for the three parameters and crossover/mutation for degradation factors follow conventional GA algorithms, with post-mutation normalization also adhering to rules.

The improved crossover operations, utilizing two different methods selected randomly, significantly increase population diversity, enhance global search capability, and preserve operator precision to some extent, facilitating the generation of globally optimal parameters.

After algorithm completion, the parameter set maximizing the likelihood function represents the optimal HMM parameter estimates under historical data conditions.

4.1 Greedy Approximation Method

For conventional HMM prediction problems, approximation algorithms and Viterbi algorithms are commonly used. Current research typically employs the latter to calculate the most probable state sequence given HMM parameters and observation sequences. However, in practical RUL prediction applications, equipment is still in service, meaning complete observation sequences from initial operation to failure are unavailable. Researchers typically substitute historical data from similar equipment to build models, input observation sequences up to a certain service time point, predict hidden states, and determine RUL through age-time distributions. This conflicts with HMM' s exponential distribution limitation, and inherent equipment differences plus state randomness reduce prediction adaptability.

Therefore, this paper proposes a novel remaining state prediction method (hereafter called greedy approximation method) based on approximation and Viterbi algorithms.

The greedy approximation method applies the state-seeking concept of approximation algorithms to finding remaining observations. Given HMM parameters θ, it seeks the most likely observation value at the next moment.

Define the probability of generating observation θ_{k+1} at time $t+1$ given observation θ_k at time t as $P(o_{t+1}=\theta_{k+1}|o_t=\theta_k)$. The mathematical description is:

$$P(o_{t+1}|o_t)=\sum_{i=1}^{N}\sum_{j=1}^{N}b_i(o_t)\cdot a_{ij}^t\cdot b_j(o_{t+1}) \quad (13)$$

where a_{ij}^t is the state transition probability at time t, which follows the three-stage degradation described above. Substituting different ϕ values calculates the probability of transitioning from observation o_t at time t to observation o_{t+1} at time $t+1$, yielding the indirect observation transition probability matrix $V_{t,t+1}$.

Since the state transition matrix degrades gradually over monitoring time points, $V_{t,t+1}$ also changes over time. For a given observation point o_t, the most probable observation at the next time point is:

$$P_{t+1}^{\max}=\max_{1\le j\le M}V_{t,t+1}(i,j) \quad (14)$$

The optimal next observation is:

$$o_{t+1}^{*}=\arg\max_{1\le j\le M}V_{t,t+1}(i,j) \quad (15)$$

The observation sequence then comprises the first t actual observations and one predicted observation: $O_{\text{new}}=\{o_1,o_2,\dots,o_t,o_{t+1}^{*}\}$.

Detailed remaining state prediction steps:

a) Input O_{old} into the Viterbi algorithm to obtain the maximum probability state path Roads* and record the final state value s^{*}.

b) Use the approximation method to find the most likely next observation o_{t+1}^{*}, append it to O_{old} to form O_{new}.

c) Input O_{new} into the Viterbi algorithm to obtain the new maximum probability state path Roads** and record the final state value s^{**}.

d) Compare s^{*} and s^{**}. If $s^{*}\neq s^{**}$, repeat steps b)-d); if $s^{*}=s^{**}$, proceed to step e).

e) The difference between the initial O_{old} and final O_{new} yields the predicted remaining observations. The state transition probability matrix at this point can be derived from the degradation factors and initial state transition probability matrix, enabling equipment RUL prediction.

4.2 Equipment Remaining Useful Life Prediction

For the maximum remaining state path Roads* obtained in Section 4.1, assuming current equipment is in state i, find the last time node t_{last} in state i within Roads*. The RUL is calculated as:

$$\text{RUL} = \sum_{j=i}^{\text{last}} \frac{D_j \cdot a_{ij}}{a_{ii} + a_{ij}} \quad (16)$$

where D_j is the historical lifetime of equipment in state j, a_{ii} is the probability of transitioning from state i to itself at the last node of current state i, and a_{ij} is the probability of transitioning from state i to state j at the last node. The total remaining life equals the sum of the remaining lifetime in the current state and lifetimes of all subsequent states.

5 Case Study

The proposed model and method are validated and evaluated through equipment health diagnosis and RUL prediction of hydraulic pumps from Caterpillar Inc. Vibration signals were collected by hydraulic accelerometers installed parallel to the pump' s rotating shaft. In the application, hydraulic pumps were contaminated with 20mg, 40mg, 60mg, and 80mg of fine dust, with vibration signal samples of approximately 1 minute collected every 10 minutes. Using 10db wavelets, vibration signals were decomposed into five levels, with dimensionality-reduced wavelet coefficients serving as input feature sequence vectors for DGHMM. The entire experimental analysis platform is Python 3 running on Windows 10.

5.1 DGHMM Data Preparation

Vibration signal monitoring data from 36 sensors are used for hydraulic pump health state diagnosis and RUL prediction. Partial wavelet-transformed data (Pump6) are shown in .

TABLE:2 Partial Wavelet Transform Data of Pump6

Feature1	Feature2	⋯	FeatureM
...	...	...	...

5.2 Experimental Parameter Estimation

The improved genetic algorithm simultaneously estimates parameters for both DGHMM and time-varying HMM. and show the initial and failure-critical state transition probability matrices for Pump6, respectively. The algorithm uses a population size of 30, crossover probability of 0.7, and mutation probability of 0.3. Considering potentially large magnitude differences in likelihood values across parameter sets, population size is reduced and iteration count increased to enhance selection pressure, while increased mutation probability ensures population diversity per generation.

TABLE:3 Initial State Transition Matrix of Pump6

state	baseline	cont1	cont2	cont3
baseline	···	···	···	···
cont1	···	···	···	···
cont2	···	···	···	···
cont3	···	···	···	···

TABLE:4 Failure Critical State Transition Matrix of Pump6

state	baseline	cont1	cont2	cont3
baseline	···	···	···	···
cont1	···	···	···	···
cont2	···	···	···	···
cont3	···	···	···	···

The likelihood iteration curves for DGHMM and time-varying HMM throughout the improved GA process are shown in [Figure 6: see original paper] (Pump6). Parameter estimation results show that the likelihood of experimental data under DGHMM' s superior parameter set exceeds that under time-varying HMM' s superior parameter set, reflecting DGHMM' s better ability to depict experimental data compared to conventional exponential accelerated degradation time-varying HMM.

5.3 Health State Diagnosis

Experimental data from Pump6 and Pump82 are vectorized and input into HMM, time-varying HMM, and DGHMM models. The Viterbi algorithm is applied to obtain the maximum probability state paths under respective experimental observations and optimal parameter sets for validation. Results are shown in , with maximum probability state path values for different models presented in .

TABLE:5 Health States Identification Results of Pump6 and Pump82

Model	Pump6 Accuracy	Pump82 Accuracy
Time-varying HMM	86%	73%
DGHMM	100%	100%

TABLE:6 Path Probabilities of Pump6 and Pump82 Under Each Model

Pump	Time-varying HMM	DGHMM
Pump6	7.32E-11	5.39E-13
Pump82	8.16E-11	1.03E-13

5.4 Remaining Useful Life Prediction

Using the proposed greedy approximation algorithm and conventional Viterbi algorithm-based RUL prediction method, the RUL of Pump6 and Pump82 under DGHMM is dynamically obtained, with results shown in [Figure 7: see original paper]. Prediction errors remain within reasonable ranges relative to actual RUL. When equipment reaches failure state cont3, operation stops, degradation ceases, and the model successfully identifies and determines RUL as 0. Although predictions exhibit some "retention phenomenon" at state transitions between Baseline and cont1, overall, the greedy approximation method based on DGHMM effectively and feasibly predicts RUL for Pump6 and Pump82.

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6 Conclusion

This paper proposes an equipment health diagnosis and RUL prediction method centered on a novel accelerated degradation model. The quasi-power relation is more conservative and stable than exponential relations as a degradation factor, better describing the gradual accelerated degradation process with increasing service age and enabling more precise state identification. The improved genetic algorithm-based parameter estimation achieves relatively good results. The proposed greedy approximation method partially breaks the conventional HMM constraint of exponential time distribution, enabling approximate RUL prediction. Consequently, the equipment health diagnosis and RUL prediction method based on improved degenerated HMM proves more effective in depicting equipment degradation and diagnostic accuracy, while remaining feasible for RUL prediction.

This paper only applied the quasi-power relation to HMM and validated the results. Future work should extend it to HSMM for further verification. To ensure optimization effectiveness, the improved genetic algorithm requires many iterations with high time complexity, which should be addressed in future improvements. Additionally, infinite loops during greedy approximation execution should be handled by setting appropriate iteration limits.

References

[1] Liu Qun, Zhang Huaping, Yu Hongkui, et al. Chinese Lexical Analysis Using Cascaded Hidden Markov Model [J]. Journal of Computer Research and Development, 2004, (08): 1421-1429.

[2] Cao Lin, Wang Dongfeng, Liu Xiaojun, et al. Face Recognition Based on Gabor Wavelets and Hidden Markov Model [J]. Control and Decision, 2005, (09): 1073-1076.

[3] Carey B, Dan M, Tarik A. Condition-based maintenance of machines using hidden markov models [J]. Mechanic Systems and Signal Processing, 2000, 14 (4): 597-612.

[4] Wang Yanfeng, Li Zuxin, Quan Lidi, et al. Cluster synchronization of Markovian complex networks with uncertain transition probabilities [J]. Control and Decision, 2018, 33 (04): 741-748.

[5] Ma Lun, Kang Jianshe, Zhao Qiang. Implementation of Equipment Residual Life Prediction Framework Based on Hidden Markov Model [J]. Computer Simulation, 2010, 27 (05): 88-91.

[6] Dong Ming. A new device health management method based on autoregressive implicit semi-Markov chain [J]. Science in China: Information Sciences, 2008, (12): 2185-2198.

[7] Liu Qian. Residual Life Prediction Based on Dynamic and Static Parameters of High Speed-Railway Catenary [D]. Sichuan: Southwest Jiaotong University, 2017.

[8] Dong M. Hidden semi-Markov model based methodology for multi-sensor equipment health diagnosis and prognosis [J]. European Journal of Operational Research, 2007, 178 (3): 858–878.

[9] Liu Qinming, Li Yaqin, Lyu Wenyuan, et al. Equipment health diagnostics and prognostics method based on adaptive HSMM [J]. Computer Integrated Manufacturing Systems, 2016, 22 (09): 2187-2194.

[10] Chen A, Wu G S. Real time health prognosis and dynamic preventive maintenance policy for equipment under aging Markovian deterioration [J]. International Journal of Production Research. 2007, 45 (15): 3351-3370.

[11] Peng Ying. A Prognosis Method Using Age-Dependent Hidden Semi-Markov Model and Systematic Maintenance Policy [D]. Shanghai: Shanghai Jiaotong University, 2011.

[12] He Zhaoming, Wang Shaoping. Remaining Lifetime Prediction Based on Time-varying State Transition Probabilities of Hidden semi-Markov Model [j]. Journal of Hunan University: Natural Sciences, 2014, 41 (08): 47-53.

[13] Yuan Yuan, Zhuo Dongfeng. Application of Hidden Semi-Markov Model in Prediction of Residual Life [J]. Computer Technology and Development, 2014, 24 (01): 184-187+191.

[14] Wu Liyun, Wu Zhengpeng, Qi Yingjian. GM (1, 1) Model for Interval Grey Number Based on Genetic Algorithm [J]. Control and Decision, 2019, 34 (02): 445-448.

[15] Krause P, Wasynczuk O, Sudhoff S, et al. Analysis of Electric Machinery and Drive Systems [M]. New York: John Wiley&Sons, lnc, 2013.

[16] Zhang Xiaoqiang, Zhu Wenhui, Kang Tieyu, et al. Optimization of Discrete Hidden Markov Fault Diagnosis Model Based on Artificial Immune Algorithm [J]. Equipment Environmental Engineering, 2019, 16 (01): 63-67.

[17] Zhang Xining, Lei Wei, Yang Yuwei, et al. Adaptive Genetic Particle Swarm Algorithm for Optimization Hidden Markov Models with Applications [J]. Journal of Xi' an Jiaotong University, 2018, 52 (08): 1-8.

Note: Figure translations are in progress. See original paper for figures.