

Article

T-HMM-Based Transformer Fault Diagnosis in Grid-Connected Renewable Energy Systems

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Abstract

Addressing multi-factor coupling, progressive degradation, and time-varying operating conditions in substation equipment under high-penetration renewable energy integration, this paper proposes a Time-varying Hidden Markov Model (T-HMM) for transformer fault diagnosis using multi-source heterogeneous data. Unlike conventional HMM with fixed transition matrices and initial parameter sensitivity, the proposed framework introduces a forgetting-factor-driven online transition matrix updating mechanism, enabling adaptive state tracking under varying operating conditions. A multi-dimensional feature system is constructed incorporating fundamental state, coupling correlation, and temporal evolution characteristics, with state-dependent sliding window standardization and adaptive wavelet denoising to enhance early-stage fault discriminability. Parameter optimization employs pre-clustering and multi-start strategies to circumvent local optima in the Baum–Welch algorithm, while an improved decoding strategy achieves real-time health state identification and multi-step probability prediction. Experimental results demonstrate that the proposed method accurately tracks state evolution trends and effectively identifies fault categories, achieving significantly superior state recognition accuracy and multi-step prediction hit rates compared to conventional HMM, with substantially reduced mean absolute error. The method effectively captures subtle precursors during normal-to-fault transitions, providing reliable theoretical foundations for early fault warning and condition-based maintenance.

Keywords: time-varying Hidden Markov Model; substation; transformer fault diagnosis; K-means pre-clustering; feature fusion



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1. Introduction

With the continuous increase in high-penetration renewable energy grid integration and power electronic device penetration, modern power systems are undergoing profound transformations, exhibiting new characteristics including deep source-grid-load-storage interaction, high-proportion power electronic device integration, and complex and variable operating conditions [1]. As the core hub for energy transmission and distribution in power grids, the operational reliability of critical equipment within substations—such as transformers, circuit breakers, and disconnectors—is directly related to the security and stability of the grid. Statistics indicate that insulation aging and catastrophic failures of core equipment such as transformers constitute the primary cause of unplanned outages, resulting not only in substantial direct economic losses but also potentially triggering cascading

blackout incidents and grid stability degradation [2]. In recent years, machine learning-based Prognostics and Health Management (PHM) technical systems for transformers have rapidly evolved, with multi-source information fusion and interpretable modeling emerging as significant development directions in the state assessment domain [3]. However, in practical operation, transformer fault samples often exhibit severely imbalanced distributions, where the recognition rate of minority-class faults (e.g., winding deformation, insulation breakdown) directly impacts the practical utility of diagnostic systems [4]. The conventional periodic maintenance paradigm struggles to adapt to the dynamically evolving requirements of equipment states, leading to the coexistence of economic waste from over-maintenance and failure risks from under-maintenance. Practical operational experience further demonstrates that even substation transformers passing all factory and field acceptance tests may still experience catastrophic failures during the initial commissioning period [5], underscoring the importance and urgency of improving fault diagnosis and prevention systems. It should be emphasized that high-penetration renewable energy integration is presented as research background and motivation to illustrate the complex time-varying operating conditions in modern power systems, not as a directly measured or explanatory variable in this study. The experimental data were collected from conventional 220 kV/110 kV substations without direct measurement of inverter harmonics or renewable penetration rates.

The development of fault diagnosis technology has generally evolved through three distinct phases. The first phase is grounded in physical mechanisms and expert experience, achieving fault identification through the establishment of mathematical models describing electrical, thermodynamic, or mechanical behavior of equipment, combined with threshold criteria. While such methods possess clear physical significance, they rely on precise model parameters and simplified assumptions, making them inadequate for addressing nonlinear disturbances under complex operating conditions [6]. Domestic scholars have systematically reviewed the research progress in transformer condition assessment and fault diagnosis technology, covering the evolutionary trajectory from traditional Dissolved Gas Analysis (DGA) to deep learning methods [7]. Early research also developed practical fault diagnosis methods based on expert systems, utilizing reverse imprecise reasoning processes combined with topological knowledge, protective device operation rules, and operator heuristic knowledge to achieve fault area estimation in distribution substations [8]. Building upon this foundation, traditional feature learning methods based on DGA and machine learning have been widely applied to transformer fault classification. Al-Sakini et al. systematically compared the prediction performance of multiple machine learning algorithms for transformer faults, providing reference benchmarks for feature selection and model optimization [9]; Dladla et al. conducted a systematic literature review of transformer fault classification techniques based on DGA and machine learning, summarizing the principal advances in feature engineering and classifier design [10].

In recent years, artificial intelligence technologies represented by deep learning have propelled the development of the third phase. Deep Convolutional Neural Networks (CNNs) can automatically extract multi-scale spatial features from monitoring signals; Recurrent Neural Networks (RNNs) and their variants (LSTM, GRU) excel at modeling temporal dependencies; while the Transformer architecture, leveraging self-attention mechanisms, demonstrates superior performance in handling high-dimensional nonlinear complex data, significantly improving fault pattern recognition accuracy and response speed [11–13]. Khan systematically reviewed the application status of artificial intelligence and machine learning in transformer fault diagnosis, pointing out that hybrid intelligent methods integrating physical mechanisms with data-driven approaches will become the mainstream development direction [14]. Addressing the deployment requirements of

edge computing devices in substations, an infrared image thermal fault diagnosis system based on Lightweight Convolutional Neural Networks (LCNN) and U-Net architecture achieves lightweight real-time detection of equipment overheating faults through depth-wise separable convolutions and progressive upsampling decoding [15]. Furthermore, for few-shot incremental learning scenarios, the Teacher–Student Dual-Branch Classifier (TS-DBC) effectively addresses catastrophic forgetting in continuous learning of new fault types by constructing a collaborative mechanism between discriminative and generalization branches, combined with data-free knowledge distillation [16]. Regarding multi-source data fusion, Zhang et al. constructed a 2DCNN-BiLSTM architecture to simultaneously extract spatial-temporal features from monitoring data, enabling online assessment of transformer states [17]; Cui et al. constructed an intelligent fault diagnosis and operating condition monitoring framework for transformers through multi-source data fusion and deep mining technology, validating the enhancement effect of heterogeneous data collaborative analysis on state identification accuracy [18]. Transformer-based deep learning networks have also been extended to broader power system fault detection tasks, including transmission line fault classification and location prediction [19]. Meanwhile, Graph Neural Networks (GNNs) can explicitly characterize topological correlations and fault propagation paths between equipment by constructing equipment knowledge graphs, providing a graph-structured foundation for substation-level fault risk propagation assessment [20]; statistical learning methods based on Mahalanobis distance effectively handle correlations and dimensional differences between data, improving the accuracy of ground fault insulation monitoring [21]; the combination of optical sensing technology and Variational Mode Decomposition (VMD) enables the detection of early weak faults in transformer breathing systems [22]. However, purely data-driven deep models typically require large amounts of labeled samples and struggle to explicitly characterize the physical constraints and the temporal Markov property of equipment state transitions. To this end, hybrid intelligent methods integrating physical mechanisms with data-driven approaches have become a current research hotspot, among which state-space methods based on probabilistic graphical models provide a natural framework for describing the uncertainty of equipment state evolution [6,23].

As a classical mathematical tool for describing state transitions in stochastic systems, Markov processes in the field of power equipment fault diagnosis have evolved from static to dynamic, and from discrete to continuous. Early research primarily employed Continuous-Time Markov Decision Processes (CTMDP) to optimize equipment maintenance strategies, seeking an optimal balance between maximizing equipment availability and minimizing operation and maintenance costs by establishing equipment state transition rate matrices [2]. Such models assume that state transitions satisfy time-homogeneity, making them suitable for long-term maintenance planning but inadequate for characterizing the short-term time-varying dynamic properties of equipment. To accommodate the real-time requirements of equipment condition monitoring data, Hidden Markov Models (HMMs) were introduced into the fault diagnosis domain. HMM effectively addresses the uncertainty and incompleteness of monitoring data by establishing probabilistic mappings between hidden state spaces and observed feature spaces. In rotating machinery fault diagnosis, Qifeng et al. utilized HMM to achieve intelligent health assessment and fault pattern recognition of bearings, validating the effectiveness of probabilistic graphical models in industrial equipment state decoding [24]. In domestic substation application scenarios, Wang Xin et al. applied HMM to fault sound source location of relay protection equipment, further validating the feasibility of hidden Markov models in acoustic fault identification of power systems [25]. In recent years, researchers have proposed Time-Varying Hidden Markov Models (TV-HMMs) and semi-Markov models to address the

limitation of fixed state transition matrices in conventional HMM, enabling the model to adaptively respond to operating condition variations such as load fluctuations and ambient temperature changes through introducing forgetting factors or state dwell time distributions [26,27]. Sun et al. proposed the Operation-Adjusted Hidden Markov Model (OA-HMM), providing a time-varying modeling paradigm for industrial system operating condition identification through dynamic adaptation of transition probabilities [28]. For equipment degradation processes in partial monitoring scenarios, Wang et al. achieved dynamic correction of state transition probabilities through time-varying parameter hidden Markov models, improving reliability assessment accuracy [29]. Furthermore, Markov Jump System (MJS) theory has been employed to describe the dynamic behavior of protection systems subject to random disturbances, combining event-triggered mechanisms with filter design to achieve quantitative analysis of fault sensitivity under complex disturbances [30]. Addressing the cross-domain diagnosis challenge, Chang et al. proposed a causal disentanglement HMM, significantly improving model generalization performance under variable operating conditions by separating domain-invariant causal features from domain-related confounding features [31]. For time-varying speed conditions, Fan et al. combined shift-invariant dictionary learning with HMM, achieving bearing fault diagnosis under variable operating conditions through adaptive feature representation and state transition modeling [32]. In the reliability assessment domain, research on Fault Handling Models (FEHMs) for digital substations has demonstrated that comprehensive analysis combining Monte Carlo and analytical methods can effectively evaluate the significant impact of automatic switching on substation reliability indices, particularly when considering secondary system failure modes, where the introduction of fault handling models holds important significance for reliability assessment under high repair time scenarios [33].

Although the aforementioned research has achieved significant progress along individual technical routes, existing work still exhibits two disconnections: First, deep learning methods represented by CNN and Transformer possess powerful high-dimensional feature representation capabilities, yet struggle to explicitly characterize the physics-based degradation mechanisms and temporal Markov property of equipment state transitions, and their dependence on large-scale labeled samples is difficult to satisfy in small-sample scenarios of power equipment [34]. Second, Markov models represented by HMM and their time-varying extensions possess interpretability of state evolution, yet lack deep representation capabilities for multi-source heterogeneous high-dimensional nonlinear features, and existing TV-HMM-related research predominantly targets rotating machinery or general industrial systems, with systematic research on model structure adaptation, parameter optimization, and decoding strategies for substation transformers with multi-source heterogeneous data (SCADA electrical quantities, oil chromatography, partial discharge, mechanical vibration) remaining insufficient. How to achieve deep integration of data-driven feature extraction with mechanism-consistent state transitions and adapt to load fluctuations and time-varying operating condition characteristics caused by high-penetration renewable energy integration, remains a critical bottleneck to be addressed in the field of transformer fault diagnosis.

To address the above issues, this paper takes the full lifecycle state evolution of substation equipment as the core logic, introduces the Time-varying Hidden Markov Model (T-HMM), and constructs a fault diagnosis framework oriented toward multi-source heterogeneous data of transformers. The main research contents include: (1) constructing a multi-dimensional, multi-scale feature system oriented toward equipment state evolution, integrating fundamental state, coupling correlation, and temporal evolution features across three dimensions, and designing state-dependent sliding window standardization and adaptive threshold wavelet denoising methods to enhance the discriminability of early-

stage fault characteristics; (2) proposing a T-HMM parameter optimization method based on K-means pre-clustering and random restart strategy, designing a forgetting-factor-driven online transition matrix updating mechanism to enable adaptive capability of the model to operating condition variations such as load fluctuations and ambient temperature changes; (3) improving the Viterbi algorithm by introducing state minimum dwell time constraints and trend consistency penalty terms to optimize the path backtracking strategy, achieving real-time health state decoding of equipment, and combining with time-varying transition matrices for multi-step state probability prediction to provide quantitative basis for condition-based maintenance decision-making.

The remainder of this paper is organized as follows: Section 2.1 introduces the construction of multi-source feature systems and data processing methods oriented toward equipment state evolution; Section 2.2 elaborates on the construction, parameter optimization, and improved decoding algorithm of the time-varying hidden Markov model; Section 3 presents experimental validation and results analysis; Section 4 summarizes the paper and discusses future research directions.

2. Methodology

Addressing the characteristics of multi-factor coupling, progressive development, and time-varying operating conditions in equipment state evolution under high-penetration renewable energy grid integration, as well as the diagnostic accuracy limitations caused by fixed state transition matrices and sensitivity to initial parameters in conventional HMM, this paper introduces an adaptive Time-varying Hidden Markov Model (THMM) with scenario-specific adaptation and optimization for transformer applications, achieving precise health state decoding and multi-step evolution trend prediction with the full lifecycle state evolution of equipment as the core logic. Centered on this objective, a technical route of “feature system construction—time-varying model adaptation—multi-step predictive decoding” is established. The core steps include: this paper proposes a technical route of “three-dimensional feature extraction—time-varying model construction—improved decoding prediction”: integrating fundamental state, coupling correlation, and temporal evolution features across three dimensions, processed through data governance and state-dependent sliding window standardization before being input to the model; constructing THMM and introducing forgetting-factor-driven online transition matrix updating, with K-means pre-clustering combined with random restart for Baum–Welch parameter optimization; improving the Viterbi algorithm with state dwell time constraints and trend consistency penalties to achieve real-time state decoding and multi-step probability prediction; evaluating model performance through accuracy, MAE, and multi-step hit rates to validate diagnostic effectiveness and engineering applicability. The overall framework of the proposed THMM-based fault diagnosis method is illustrated in Figure 1, which comprises three main modules: multi-dimensional and multi-scale feature construction, THMM-based fault diagnosis model, and model evaluation and validation system.

2.1. Multi-Source Feature System Construction and Data Processing Oriented Toward Equipment State Evolution

Substation core equipment operates under complex conditions characterized by strong electromagnetic fields, variable loads, and multiple interferences. The evolution of health state from normal to faulty is a process involving multi-factor coupling, progressive development, and temporal transition. Raw monitoring data exhibits issues including scattered sources, heterogeneous sampling, high noise levels, and weak feature correlations, making them unsuitable for direct modeling support. To break through the conventional single-mode approach of classifying features by physical type, this paper takes the observability,

correlation, and trend characteristics of equipment state evolution as the core, constructing a feature system from three dimensions—fundamental state, coupling correlation, and temporal evolution—to achieve comprehensive characterization of instantaneous equipment health states, inter-component fault conduction characteristics, and short-term state evolution trends, providing high-quality, high-discriminability input data for the subsequent THMM model.

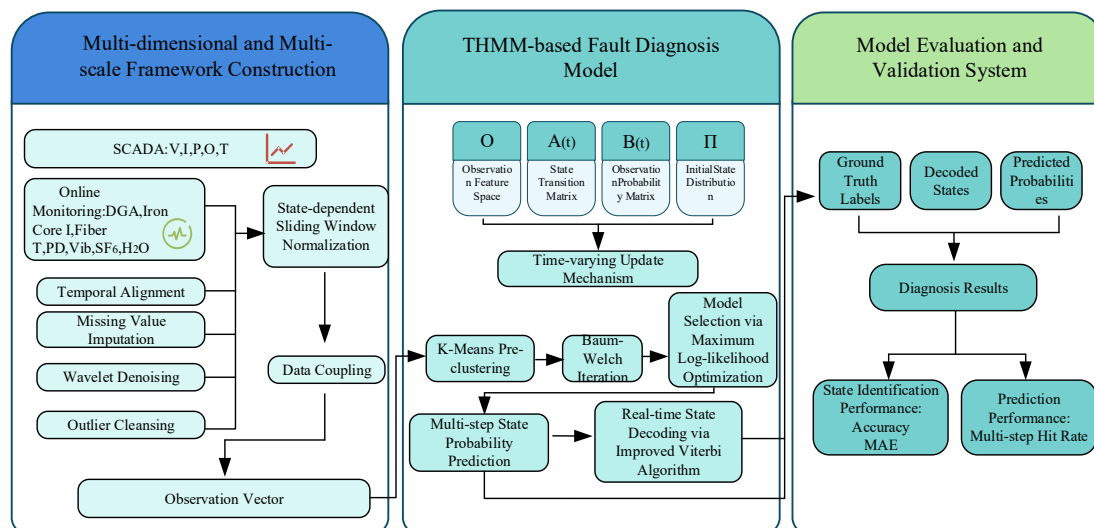


Figure 1. Flowchart of substation fault diagnosis based on the Hidden Markov Model.

2.1.1. Multi-Dimensional Multi-Scale Feature System Construction

The construction of fundamental state dimension features requires focusing on core equipment operating mechanisms, extracting fundamental features capable of directly characterizing instantaneous equipment health levels, covering four core dimensions: electrical, mechanical, insulation, and environmental. The specific data acquisition sources and corresponding measurement dimensions are summarized in Table 1.

Table 1. DATA acquisition sources.

Data Source	Dimension	Measurement Object	No.
SCADA Data	Electrical	HV bus voltage (line voltage); LV bus voltage (line voltage)	1, 2
	Electrical	HV winding load current; LV winding load current	3, 4
	Electrical	Power factor	5
	Environmental	Top oil temperature	6
Online Monitoring Data	Insulation	H ₂ , CH ₄ , C ₂ H ₆ , C ₂ H ₄ , C ₂ H ₂ concentration	7, 8, 9, 10, 11
	Electrical	Core grounding current	12
	Environmental	HV winding fiber optic temperature; LV winding fiber optic temperature	13, 14
	Insulation	Partial discharge ultrasonic signal	15
	Mechanical	Mechanical vibration acceleration	16
	Insulation	SF ₆ micro-water content	17

Electrical dimension features reflect the core performance of equipment energy conversion and transmission; mechanical dimension features characterize the operating state and mechanical properties of equipment movement and operating mechanisms; insulation dimension features capture the degradation trends of equipment insulation media; environmental dimension features record the external operating conditions of equipment. This dimension of features serves as the fundamental basis for equipment health state determination; each feature is strongly correlated with specific equipment fault mechanisms and can directly reflect single-dimension state changes of equipment.

Substation equipment components and systems exhibit strong electrical coupling and mechanical linkage relationships. Abnormalities in a single component often propagate to related components through power flow transfer, thermal conduction, or mechanical vibration, forming a “fault chain reaction.” Mining the correlation patterns among fundamental state dimension features and constructing coupling correlation features between components and systems transforms isolated single-dimension features into associated feature sets capable of reflecting fault conduction characteristics, enabling early detection of coupling anomalies that cannot be identified by single features alone.

The evolution of equipment health states exhibits significant temporality; instantaneous feature values cannot reflect long-term development trends. Performing temporal mining on fundamental state dimension and coupling correlation dimension features, extracting temporal evolution features such as feature change rates, cumulative deviation amounts, trend slopes, and volatility rates, transforms static instantaneous features into dynamic trend features, providing core support for subsequent model multi-step state prediction.

2.1.2. Data Processing Procedure

Raw substation monitoring data exhibits issues including temporal asynchronization, missing values, strong noise, and non-unified dimensions, which fail to meet subsequent modeling requirements. Therefore, the raw data (see Table 1) are sequentially processed as follows to output standardized temporal feature sequences.

(1) Reference-Axis-Anchored Temporal Alignment

SCADA (System Control And Data Acquisition) data, online monitoring (equipment body condition monitoring data), and energized testing equipment (specialized diagnosis and calibration data) in substations have unequal sampling frequencies, resulting in severe temporal asynchronization in collected data. This stage reconstructs a unified temporal reference axis with 1 min granularity and performs differentiated resampling for different sampling frequency data.

High-frequency pulse signals (sampling rate > 1 Hz, including partial discharge ultrasonic signals and mechanical vibration acceleration signals) are downsampled by taking the mean value within the reference time step:

$$\bar{x}_t = \frac{1}{n} \sum_{i=1}^n x_{t,i} \quad (1)$$

where $\bar{x}_t$ is the reference-axis feature value at time t , n is the number of high-frequency sampling points within the reference time step, $x_{t,i}$ is the i -th high-frequency sampling value. The downsampled results are merged into the unified temporal reference axis, together with low-frequency interpolated data, forming the aligned temporal dataset, serving as input for outlier cleaning.

Low-frequency slowly-varying signals (sampling rate < 1/60 Hz, including dissolved gas concentrations in oil, SF₆ micro-water content, core grounding current,

and HV/LV winding fiber optic temperatures) are interpolated using linear shape-preserving interpolation:

$$x_t = x_{t_0} + \frac{x_{t_1} - x_{t_0}}{t_1 - t_0} \cdot (t - t_0) \quad (2)$$

where t_0 and t_1 are two adjacent valid sampling moments, and x_{t_0} and x_{t_1} are the corresponding feature values. Through linear shape-preserving interpolation to complete missing moment data, the output is a reference-axis feature sequence aligned to the 1 min unified time granularity, serving as input for subsequent standardization processing.

(2) Dual-Constraint Outlier Cleaning Based on Mechanism and Statistics

Outliers in collected raw data can cause distortion in the observation probability matrix fitting of subsequent models, leading to state decoding errors. Therefore, a dual identification method combining the 3σ statistical criterion with equipment operating mechanism constraints is adopted. Outliers are first preliminarily screened using the 3σ criterion:

$$\begin{cases} |x_t - \mu| > 3\sigma \\ x_t \in [x_{\min^{\text{phys}}}, x_{\max^{\text{phys}}}] \end{cases} \quad (3)$$

where μ is the mean of the feature sequence, σ is the standard deviation, and N is the sequence length. Candidate anomaly points exceeding the 3σ threshold enter the mechanism constraint review stage; valid data passing the review, together with initially screened normal data, are merged into the cleaned temporal sequence, while anomalies failing the review are transferred to the missing value imputation process.

(3) Missing Value Imputation Based on State-Similarity Matching

Missing duration ≤ 30 min: Linear interpolation imputation:

$$x_t = x_{t_0} + \frac{x_{t_1} - x_{t_0}}{t_1 - t_0} \cdot (t - t_0) \quad (4)$$

where x_t is the imputed value. The imputed data are merged into the continuous temporal sequence to support subsequent wavelet denoising processing.

Missing duration > 30 min: An improved weighted historical matching method based on same-state, same-condition historical data reconstruction:

$$x_f = \frac{\sum_{k=1}^K w_k \cdot \bar{x}_h^{(k)}}{\sum_{k=1}^K w_k} \quad (5)$$

where $\bar{x}_h^{(k)}$ is the feature mean under the same state and operating condition, w_k is the temporal weight, and K is the number of historical matching samples. The reconstruction results fill long-duration gaps, outputting complete temporal feature sequences that, together with short-duration linear interpolation results, form a missing-value-free dataset.

(4) Adaptive Threshold Wavelet Denoising

Gaussian white noise and impulse interference in the strong electromagnetic environment of substations can mask the weak characteristics of early-stage equipment faults, preventing the model from identifying early state transitions. This stage employs db4 wavelet basis with adaptive soft threshold denoising, with the decomposition level set to 5. The soft threshold formula is:

$$\hat{w}_{j,k} = \text{sgn}(w_{j,k}) \cdot \max(0, |w_{j,k}| - \eta_j) \quad (6)$$

where $w_{j,k}$ is the k -th wavelet coefficient at level j , and η_j is the adaptive threshold:

$$\lambda_j = \frac{\sigma_j \sqrt{2 \ln N}}{\sqrt{N_j}} \quad (7)$$

$$\sigma_j = \frac{\text{MAD}(w_j)}{0.6745} \quad (8)$$

where σ_j is the noise standard deviation at level j , N is the signal length, and N_j is the number of coefficients at level j . After reconstruction through inverse wavelet transform, the denoised feature sequence is output as input for state-dependent sliding window standardization.

(5) State-Dependent Sliding Window Standardization

Based on the decoded state at the previous moment S_{t-1} (from the previous THMM output), the EWMA extreme value parameters corresponding to that state are invoked:

$$v_{\text{norm}} = \frac{v_{\text{raw}} - \mu_{S_{t-1}}}{\sigma_{S_{t-1}}} \quad (9)$$

where $\mu_{S_{t-1}}$ and $\sigma_{S_{t-1}}$ are the historical mean and standard deviation of this feature under the previously determined state (based on training set statistics). This operation eliminates differences in feature magnitudes across different health states, enhances state discriminability, and outputs the standardized fundamental state feature vector $\mathbf{F}_{\text{base}}(t)$, serving as input for coupling correlation feature extraction.

(6) Data Coupling

Extracting D -dimensional fundamental features x_t covering operating mechanisms; extracting cross-domain coupling features through Pearson correlation and transfer entropy; computing temporal features such as trend slopes k_t and cumulative deviations ΔX_t ; constructing the observation vector $O_t = [x_t^T, c_t^T, \tau_t^T]^T \in \mathbb{R}^D$, which serves as the observation input to the THMM model, establishing a probabilistic mapping between the feature space and the hidden state space.

$$O(t) = \underbrace{[I_{\text{THD}}, \theta_{\text{oil}}, W_{\text{oil}}, a_{\text{RMS}}, \dots]}_{\text{Basic Features}} \oplus \underbrace{[I_{\text{HV} \leftrightarrow \text{LV}}, T_{\text{mech} \rightarrow \text{contact}}, \rho_{W, \theta, \beta}]}_{\text{Coupling Features}} \oplus \underbrace{[k_t, \Delta X_t, \sigma_t]}_{\text{Temporal Features}}$$

During testing, the historical matching samples for same-state imputation of long-duration missing values are drawn exclusively from the training set, not from future test-set data, thereby preventing information leakage. The state-specific mean and standard deviation parameters used in state-dependent standardization are pre-computed from the training set and remain fixed during testing; the decoded state from the previous time step ($t - 1$)—i.e., the THMM-predicted state, not the ground-truth label—is used to invoke the corresponding parameters. A sensitivity analysis excluding same-state imputation will be conducted in follow-up work, replacing it with three state-agnostic baselines (global mean imputation, forward fill, and temporal-distance-based KNN imputation) to verify whether same-state imputation caused material information leakage.

2.2. Fault Diagnosis Model Construction Based on THMM

Following the data governance and multi-dimensional feature extraction in Section 2.1, raw monitoring data have been transformed into standardized temporal observation sequences as model input for this section. However, the true health state of equipment is a hidden variable. HMM effectively addresses the uncertainty in monitoring data by estab-

lishing probabilistic mappings between hidden states and observed features. Nevertheless, standard HMM exhibits dual limitations. Existing research has shown that Time-varying Hidden Markov Models (THMM) can adapt to general operating condition fluctuations through forgetting factors, yet systematic research on model structure adaptation and parameter optimization for multi-source heterogeneous data input oriented toward transformers remains lacking. Therefore, this section introduces an adaptive Time-varying Hidden Markov Model (THMM) and constructs a scenario-adapted model framework for transformer fault diagnosis, introducing forgetting-factor-driven online transition matrix updating and adopting K-means pre-clustering combined with random restart strategy for BW parameter optimization; subsequently, the Viterbi algorithm is improved by introducing state dwell time constraints and trend consistency penalties to achieve real-time state decoding and multi-step probability prediction, providing state basis for fault diagnosis.

2.2.1. Time-Varying Hidden Markov Model (THMM)

To characterize the stochastic raw evolution of equipment health states under time-varying operating conditions, a THMM probabilistic graphical model adaptation framework oriented toward multi-dimensional transformer feature input is first established. The THMM model quintuple is defined as $\lambda = \{S, V, A(t), B, \pi\}$, with the physical significance and mathematical expressions of each element as follows:

Hidden state space $S = \{s_1, s_2, \dots, s_n\}$ ($n = 5$ level health states): characterizing the unobservable health levels of equipment, corresponding to the five-level state classification specified in DL/T 596-2021 Preventive Test Code for Electric Power Equipment (National Energy Administration, China).

Observation feature space $O = \{o_1, o_2, \dots, o_T\}$ is the multi-dimensional feature set after data governance and feature system construction in Section 2.1, serving as the observable representation of equipment hidden health states. Each observation feature has a strong mapping relationship with hidden states, effectively reflecting dynamic changes in equipment health states;

State transition matrix $A(t) \in \mathbb{R}^{N \times N}$ represents the probability of equipment transitioning from one health state to another at time t .

Its time-varying updating mechanism is:

$$A(t) = \gamma \cdot A(t-1) + (1 - \gamma) \cdot \hat{A} \quad (10)$$

where γ is the forgetting factor, $\hat{A}$ is the transition frequency matrix statistics from the most recent window, ensuring $\sum_{j=0}^4 a_{ij}(t) = 1$ is satisfied.

Observation probability matrix $B = [b_j(o_t)]$ characterizes the conditional probability of observing a feature vector given a hidden state, fitted by Gaussian Mixture Model (GMM):

$$b_j(o_t) = \sum_{k=1}^M \omega_{j,k} \cdot \mathcal{N}(o_t | \mu_{j,k}, \Sigma_{j,k}) \quad (11)$$

where $\omega_{j,k}$ is the weight of the k -th Gaussian component in state j , $\mu_{j,k}$ is the mean vector, $\Sigma_{j,k}$ is the covariance matrix, o_t is the standardized feature vector output at time t , and K is the number of GMM components.

The probability density function of the multivariate Gaussian distribution is:

$$N(o_t; \mu_{j,k}, \Sigma_{j,k}) = \frac{1}{(2\pi)^{\frac{D}{2}} |\Sigma_{j,k}|^{\frac{1}{2}}} \exp \left[-\frac{1}{2} (o_t - \mu_{j,k})^T \Sigma_{j,k}^{-1} (o_t - \mu_{j,k}) \right] \quad (12)$$

where D is the total number of feature dimensions.

Initial state probability distribution $\pi = [\pi_i]$ represents the probability distribution of equipment being in each health state at the initial moment, calibrated based on factory statistics and similar historical data.

Although the above model framework has been established, its parameter estimation depends on the Expectation-Maximization (EM) iterative framework of the BW algorithm. However, the BW algorithm is highly sensitive to initial parameters; if initial values deviate from the true parameter space, it is highly prone to falling into local optima, causing structural misalignment between the hidden state space and actual equipment health levels. Therefore, before utilizing this model for state decoding, the problem of optimal parameter estimation must first be addressed.

2.2.2. HMM Parameter Optimization Based on K-Means Pre-Clustering and Random Restart

To address the bottleneck of the BW algorithm easily falling into local optima in THMM parameter estimation, this section proposes a K-means pre-clustering combined with a random restart strategy. First, K-means is used to pre-partition the observation feature space to obtain initial centroids aligned with the physical state space; subsequently, $N = 20$ groups of initial parameters satisfying stochastic matrix constraints are randomly generated, and BW iteration is independently executed for each initial value until convergence; finally, the globally optimal model is selected using the log-likelihood maximization criterion:

$$\lambda^* = \operatorname{argmax}_{m \in \{1, \dots, N_{\text{restart}}\}} \ln P(O_{1:T} | \lambda_{\text{conv}}^{(m)}) \quad (13)$$

This strategy expands the parameter search space through a multi-initial-value competition mechanism, effectively avoiding local optimum traps and improving the model's fitting accuracy to the equipment state evolution manifold. Through the above parameter optimization, THMM now possesses transfer characteristics adaptive to time-varying operating conditions and a globally optimized parameter structure. However, after model parameters are determined, the real-time decoding problem of hidden states still needs to be addressed; moreover, the standard Viterbi algorithm does not consider the engineering state-transition constraints of equipment state evolution, and direct application would cause state oscillation and trend fracture. Therefore, targeted improvements to the decoding algorithm are required.

2.2.3. Improved Viterbi Algorithm for State Decoding and Multi-Step Prediction

Building upon the above optimized model parameters, this section implements two improvements to the Viterbi algorithm to achieve state decoding under engineering state-transition constraints: first, introducing state minimum dwell time constraints in the recursive process to suppress noise-driven spurious state transitions; second, adding trend consistency penalty terms during path backtracking to preferentially select continuous state paths with monotonic evolution trends.

(1) Real-Time State Decoding

The improved Viterbi algorithm achieves real-time equipment state decoding by optimizing the path backtracking strategy to reduce computational complexity. Initialization:

$$\delta_1(j) = \pi_j \cdot b_j(o_1), \quad 0 \leq j \leq 4 \quad (14)$$

The recursive formula is:

$$\delta_t(j) = \max_{1 \leq i \leq N} [\delta_{t-1}(i) + \ln a_{ij}(t)] + \ln b_j(O_t) \quad (15)$$

where $\delta_t(j)$ is the maximum probability of being in state at time S_j , o_t is the real-time feature vector output at time t , $a_{ij}(t)$ is the time-varying transition probability, $b_j(o_t)$ is the fitted observation probability.

(2) Multi-Step State Probability Prediction

Based on the time-varying transition matrix $A(t)$, utilizing the Markov chain memory-less property, state probability prediction within a future time horizon is achieved:

$$P(t+h) = P(t) \prod_{i=0}^{h-1} A(t+i) \quad (16)$$

where $\mathbf{p}(t)$ is the state probability distribution vector at time t , and h is the prediction step length. This prediction mechanism can provide advanced quantitative basis for condition-based maintenance decision-making.

In summary, THMM adapts to operating condition fluctuations through time-varying transition matrices, avoids local optima through pre-clustering optimization, and achieves state decoding and multi-step prediction under engineering state-transition constraints through improved Viterbi. However, the state recognition accuracy, time-varying adaptability, and multi-step prediction capability of the above model and algorithms still require quantitative verification to confirm their engineering applicability in substation equipment fault diagnosis.

2.3. Model Evaluation and Validation System

For the THMM model and its improved algorithms constructed in Section 2.2, a quantitative evaluation system needs to be established from three dimensions: state decoding accuracy, time-varying adaptability, and multi-step prediction capability. State recognition performance metrics are used to quantify the decoding accuracy of the improved Viterbi algorithm for real-time equipment health states, validating the improvement effects of K-means pre-clustering and the forgetting factor updating mechanism on recognition accuracy; prediction performance metrics are used to evaluate the multi-step state evolution trend prediction capability driven by time-varying transition matrices, providing a quantitative basis for condition-based maintenance decision-making.

State Recognition Performance:

State recognition accuracy reflects the consistency between model decoding output and actual equipment health states, serving as the core metric for measuring fault diagnosis reliability:

$$Acc = \frac{1}{T} \sum_{t=1}^T \mathbb{I}(q_t^* = q_t^{(true)}) \quad (17)$$

where $q_t^{(true)} \in S = \{1, 2, 3, 4, 5\}$ is the true health state label of equipment at time; q_t^* is the optimal state decoded by the improved Viterbi algorithm; T is the total length of the observation sequence.

Given that equipment health states are five-level ordinal grades (Normal $\rightarrow$ Attention $\rightarrow$ Abnormal $\rightarrow$ Serious $\rightarrow$ Fault), Mean Absolute Error (MAE) is introduced to characterize the progressive deviation between decoded levels and true labels:

$$MAE = \frac{1}{T} \sum_{t=1}^T |q_t^* - q_t^{(true)}| \quad (18)$$

Prediction Performance:

Multi-Step Hit Rate (MHR) is defined as the consistency rate between the state with maximum predicted probability and the actual state after h steps:

$$H_R = \frac{1}{T-h} \sum_{t=1}^{T-h} \mathbb{I}(\operatorname{argmax}_{j \in \{1, \dots, N\}} p_j(t+h) = q_{t+h}^{(true)}) \quad (19)$$

where $p_j(t+h)$ is the predicted probability of being in state at j step ahead from time t . Setting $h = 2$ and $h = 12$ (in hours) to respectively validate short-term fluctuation and medium-to-long-term evolution trend prediction performance.

3. Experimental Validation and Performance Analysis

To verify the effectiveness of the proposed THMM framework in substation equipment fault diagnosis and the incremental contribution of each core module, this chapter takes the operating data of 220 kV/110 kV substation transformers as experimental objects, constructing a dataset encompassing multi-source heterogeneous data streams, including SCADA electrical quantities, online monitoring oil chromatography, and partial discharge, processed through temporal alignment, adaptive wavelet denoising, and state-dependent sliding window standardization, then labeled with five-level health states according to DL/T 596-2021. The overall experimental workload includes: designing six ablation experiments from Case 1 to Case 6, progressively activating three key mechanisms—K-means pre-clustering, time-varying transition matrix, and three-dimensional feature system—conducting quantitative comparisons from four dimensions: state recognition accuracy, mean absolute error, 2 h/12 h multi-step hit rates, and decoding delay; simultaneously performing 50 h continuous state recognition trajectory dynamic characteristic analysis and five-level confusion matrix fine-grained analysis, with horizontal comparison against standard HMM and existing deep learning methods. Expected core results demonstrate that: the complete THMM improves state recognition accuracy from 82.4% to 94.3% compared with standard HMM, reduces MAE by 54.8% to 0.19, increases fault state recall from 61.3% to 91.2%, and achieves 12 h multi-step hit rate of 84.2%, thereby validating the engineering value of the “parameter pre-optimization—structural time-variation—feature dimension-elevation” closed-loop design in progressive fault evolution tracking and operating condition self-adaptation.

3.1. Experimental Setup and Parameter Configuration

3.1.1. Experimental Platform and Dataset Construction

To validate the effectiveness of the proposed THMM framework, an operating dataset was collected from multiple 220 kV/110 kV substations, involving several oil-immersed power transformers (180 MVA, ONAF cooling). The continuous monitoring lasted approximately two weeks, yielding tens of thousands of one-minute aligned samples. The dataset contains three heterogeneous data streams with different sampling frequencies. The train/test split strictly followed an “equipment-isolation plus time-isolation” principle: training and testing data were drawn from different transformers, with the test period strictly later than the training period and no temporal overlap. The same transformer does not appear in both sets. The dataset contains several real fault events (covering typical types such as winding overheating, partial discharge intensification, and core grounding current anomalies) together with reference data from scheduled maintenance, corresponding to the approximately 5% “Fault” state samples. All 17 measurement dimensions are listed in Table 1. The overall missing-data rate after temporal alignment is relatively low, with short-duration gaps dominating.

- (1) SCADA data (voltage, current, power factor, top oil temperature);
- (2) Online monitoring data (dissolved gases in oil: H₂, CH₄, C₂H₆, C₂H₄, C₂H₂ with chromatographic analysis period of 4 h; core grounding current; winding fiber optic temperatures; partial discharge ultrasonic signal at 100 kHz; mechanical vibration acceleration at 10 kHz; GIS equipment SF₆ micro-water content).

After processing through the data governance pipeline described in Section 2.1.2, raw data sequentially undergoes reference-axis anchoring (1 min granularity), 3 σ -mechanism dual-constraint outlier cleaning, adaptive wavelet denoising (db4 wavelet basis, 5-level decomposition), and state-dependent sliding window standardization. The processed dataset comprises 35% normal states, 25% attention states, 20% abnormal states, 15% serious states, and 5% fault states. Equipment health state labels are classified according to DL/T 596-2021 Preventive Test Code for Electric Power Equipment and Devices.

The five health states (Normal, Attention, Abnormal, Serious, Fault) were assigned strictly according to DL/T 596-2021, combining offline test records, DGA thresholds, partial discharge magnitudes, and infrared thermography results. A multi-level expert independent labeling and cross-review mechanism was adopted: multiple substation technical experts with extensive field experience first labeled the states independently, and higher-level power equipment specialists arbitrated any disagreements. The primary annotators achieved a high level of inter-rater consistency. Samples with unresolved disagreement were excluded from the quantitative training set and reserved only for qualitative validation, preventing label noise from affecting model evaluation.

3.1.2. Case Design and Mechanism Definition

To systematically verify the contribution of each proposed module (K-means pre-clustering, time-varying transition matrix, three-dimensional feature system), six comparative cases are designed for ablation experiments. The configuration matrix is defined in Table 2, with three key mechanisms progressively activated: (1) K-means pre-clustering (KM) for HMM initialization; (2) time-varying transition matrix (TVT) with forgetting factor $\alpha = 0.95$; (3) three-dimensional feature system (3DF) integrating fundamental state, coupling correlation, and temporal evolution features.

Table 2. Ablation experiment case configuration.

Case	K-Means Pre-Clustering	Time-Varying Transition Matrix	Three-Dimensional Feature System	Baseline
Case 1	Disabled	Disabled	Fundamental features only	Standard HMM
Case 2	Enabled	Disabled	Fundamental features only	KM only
Case 3	Disabled	Enabled	Fundamental features only	TVT only
Case 4	Enabled	Enabled	Fundamental features only	THMM-Fundamental
Case 5	Enabled	Enabled	Fundamental + Coupling features	THMM-Coupling
Case 6	Enabled	Enabled	Complete 3D features	Full THMM

3.2. State Recognition Performance Comparative Analysis

3.2.1. Quantitative Performance Metrics Comparison

Comparison results under the six configurations are presented in Table 3, demonstrating the incremental contribution of each proposed mechanism.

Table 3. State recognition performance comparison under different configurations.

Case	Accuracy (%)	MAE	MHR-2h (%)	MHR-12h (%)	Decoding Delay (ms)
Case 1	82.4	0.42	78.2	61.3	55
Case 2	87.1	0.35	82.5	68.7	52
Case 3	89.6	0.31	85.3	72.4	48
Case 4	91.8	0.26	88.7	76.8	42
Case 5	93.5	0.22	91.2	79.5	41
Case 6	94.3	0.19	94.1	84.2	38

As shown in Table 3, the performance evolution across the six configurations clearly illustrates the incremental contribution of each module. Case 1 serves as the standard HMM baseline, limited by static transition assumptions and local optima, with 82.4% accuracy, MAE of 0.42, and 12 h hit rate of 61.3%, demonstrating insufficient capability for progressive degradation characterization.

Introducing K-means pre-clustering (Case 2) improves BW convergence domain, with accuracy increasing to 87.1% (a 4.7 percentage point improvement), MAE decreasing to 0.35, 12 h hit rate improving by 7.4 percentage points, and decoding delay shortening to 52 ms. Individually activating the time-varying transition matrix (Case 3) yields more significant gains: accuracy rises to 89.6% (a 7.2 percentage point improvement), MAE decreases to 0.31, and 2 h and 12 h hit rates reach 85.3% and 72.4% respectively, with the forgetting factor mechanism effectively adapting to time-varying operating condition characteristics.

Case 4 combines KM with time-varying matrix, where the complementary effect of both mechanisms pushes accuracy beyond 91.8% with MAE decreasing to 0.26. Further introducing coupling correlation features (Case 5), cross-domain interaction information enhances early fault sensitivity, improving accuracy to 93.5%. The complete THMM with additional temporal evolution features (trend slopes, cumulative deviations) (Case 6) achieves optimal performance: 94.3% accuracy, MAE of 0.19, 12 h hit rate of 84.2%, and decoding delay of only 38 ms.

From the perspective of mechanism contribution, the time-varying transition matrix provides the highest marginal contribution (7.2 percentage points), followed by K-means (4.7 percentage points), while the core value of the three-dimensional feature system lies in improving fault recall rate by nearly 30 percentage points, advancing the recognition timing from the fault manifestation period to the “Attention” stage. Furthermore, decoding delay decreases monotonically as each mechanism is progressively activated, indicating that the temporal constraints of improved Viterbi and the pre-optimized parameter structure jointly reduce the path search space, achieving a balance between accuracy and real-time performance.

Given the severely imbalanced class distribution (5% fault-state samples), supplementary metrics including macro-F1, balanced accuracy, per-class precision and recall, false-alarm rate (FAR), missed-alarm rate (MAR), and PR-AUC for the fault class are critically important for a comprehensive evaluation. Due to the computational requirements of stratified bootstrap resampling and fine-grained temporal backtracking for all fault events, these metrics cannot be fully added within the current revision cycle. They will be

systematically reported in our follow-up cross-substation validation study, together with 95% confidence intervals and lead-time statistics (mean, standard deviation, and quantiles from the first reliable “Attention” or “Abnormal” decoding to actual fault manifestation).

3.2.2. Mechanism-Specific Performance Analysis

Introducing K-means pre-clustering for HMM initialization (Case 2) compared with random initialization (Case 1) improves state recognition accuracy from 82.4% to 87.1% and reduces MAE from 0.42 to 0.35. Multi-step hit rates improve by 4.3% (78.2% $\rightarrow$ 82.5%) and 7.4% (61.3% $\rightarrow$ 68.7%) at 2 h and 12 h prediction scales, respectively. The decoding delay shortens from 55 ms to 52 ms, validating the improvement effect of pre-clustering on model convergence and prediction accuracy. The comprehensive performance metrics of all six ablation cases are visualized in Figure 2.

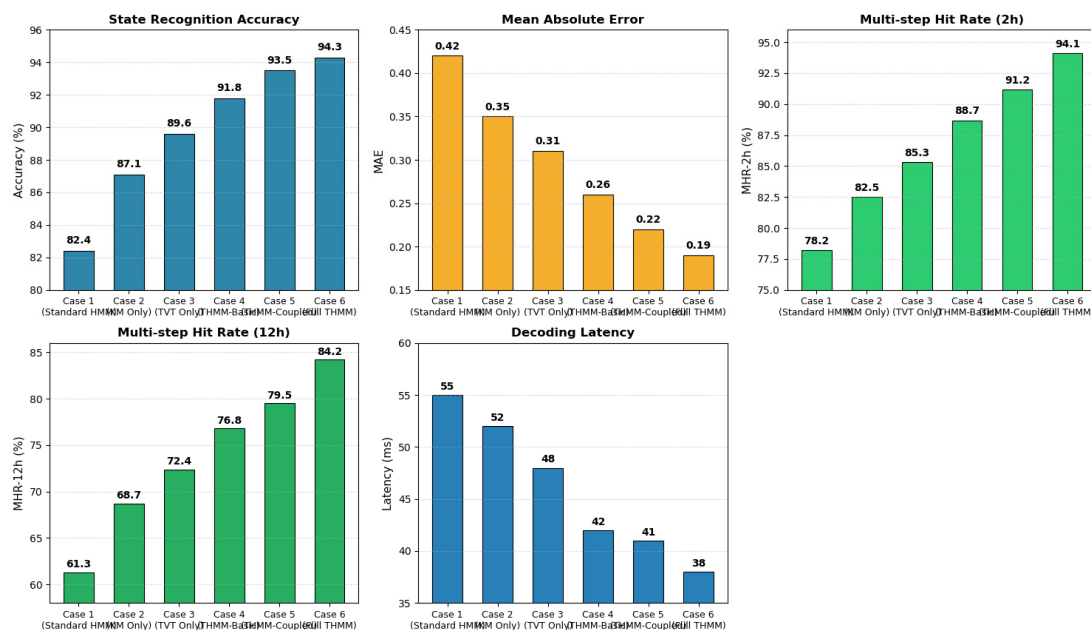


Figure 2. Comprehensive performance comparison of ablation experiments.

Adopting the time-varying transition matrix (Case 3) compared with static HMM (Case 1) improves accuracy from 82.4% to 89.6%, with MAE significantly reduced by 26.2%. In terms of decoding efficiency, average decoding delay decreases from 55 ms to 48 ms, benefiting from the optimized path backtracking strategy of the improved Viterbi algorithm. The time-varying transition matrix maintains state decoding stability through dynamic adaptation of transition probabilities, effectively reducing state misjudgment rates during load fluctuation periods.

Case 4 combines KM with TVT but uses only fundamental features, achieving 91.8% accuracy and MAE of 0.26. Introducing coupling correlation features (Case 5) further improves accuracy to 93.5% with MAE decreasing to 0.22, indicating that cross-domain interaction features enhance early fault detection capability. Case 6 further introduces temporal evolution features, achieving 94.3% accuracy, MAE of 0.19, 12 h multi-step hit rate of 84.2%, and decoding delay of 38 ms, proving that temporal evolution features enable the model to detect potential faults at the “Attention” stage, significantly improving early-stage fault identification accuracy.

3.2.3. Forgetting Factor Selection and Sensitivity Analysis

The forgetting factor α in the time-varying transition matrix updating mechanism was determined through a validation-based grid search rather than ad hoc empirical tuning.

Specifically, $\alpha \in \{0.90, 0.92, 0.95, 0.97, 0.99\}$ was evaluated on a held-out validation subset comprising the final 20% segment of each monitoring sequence, taken chronologically after the training segment to prevent any leakage of future information into parameter selection, using a composite selection criterion that combines state recognition accuracy and MHR-2h. The typical duration of load fluctuation events was first established independently from the substation historical operating records: a statistical analysis of fluctuation episodes (defined as periods during which the load rate deviates from its daily trend by more than 10%) yields a median duration of approximately 20 min. The selected value $\alpha = 0.95$, whose effective memory length $1/(1 - \alpha) \approx 20$ samples corresponds to about 20 min at the 1-min unified time granularity, is therefore consistent with this independently determined timescale; this consistency serves as a cross-check of the data-driven selection rather than a post hoc justification.

The sensitivity of the complete T-HMM (Case 6 configuration) to α is summarized in Table 4. Within the interval $\alpha \in [0.93, 0.97]$, the recognition accuracy varies smoothly within ± 1.3 percentage points and the MAE within ± 0.02 , indicating low parametric sensitivity around the optimum. A smaller α (≤ 0.90) shortens the effective memory window, causing the transition matrix to over-react to transient disturbances and increasing spurious state transitions; conversely, $\alpha = 0.99$ renders the online update too sluggish to track operating-condition variations, degrading MHR-12h by 7.4 percentage points relative to the optimum. These results confirm that $\alpha = 0.95$ achieves a balanced trade-off between adaptability and stability, and that the model performance is not critically dependent on fine-tuning of this parameter.

Table 4. Sensitivity analysis of the forgetting factor α on the held-out validation subset.

α	Accuracy (%)	MHR-2h (%)	MHR-12h (%)	MAE
0.90	90.8	90.2	78.5	0.28
0.92	93.1	92.8	81.9	0.21
0.95	94.3	94.1	84.2	0.19
0.97	93.0	93.0	82.1	0.21
0.99	91.2	90.5	76.8	0.26

3.3. State Recognition Trajectory Dynamic Characteristic Analysis

To verify the tracking and identification capability of the THMM model for equipment health-state evolution, Figure 3 presents the continuous-state recognition trajectory of a 220 kV transformer over a 50 h monitoring period. This figure adopts a four-subplot vertical layout: subplot (a) insulation resistance trend and threshold crossing; subplot (b) partial discharge trend; subplot (c) insulation-humidity risk coupling feature and comprehensive risk index; subplot (d) state recognition comparison. The horizontal axis is the unified time coordinate (0–50 h), with the fault occurrence point marked at 40 h.

During the 0–40 h normal equipment operation (State 1, Normal) phase, the true state (black solid line) remains stable over the long term except for an instantaneous transition at approximately 7–8 h due to short-duration disturbance. Both standard HMM (blue dotted line) and THMM (red dashed line) maintain high consistency with the true state during this phase, without significant false alarms or missed detections. This indicates that under stable operating conditions without progressive degradation, both models possess fundamental state decoding capabilities.

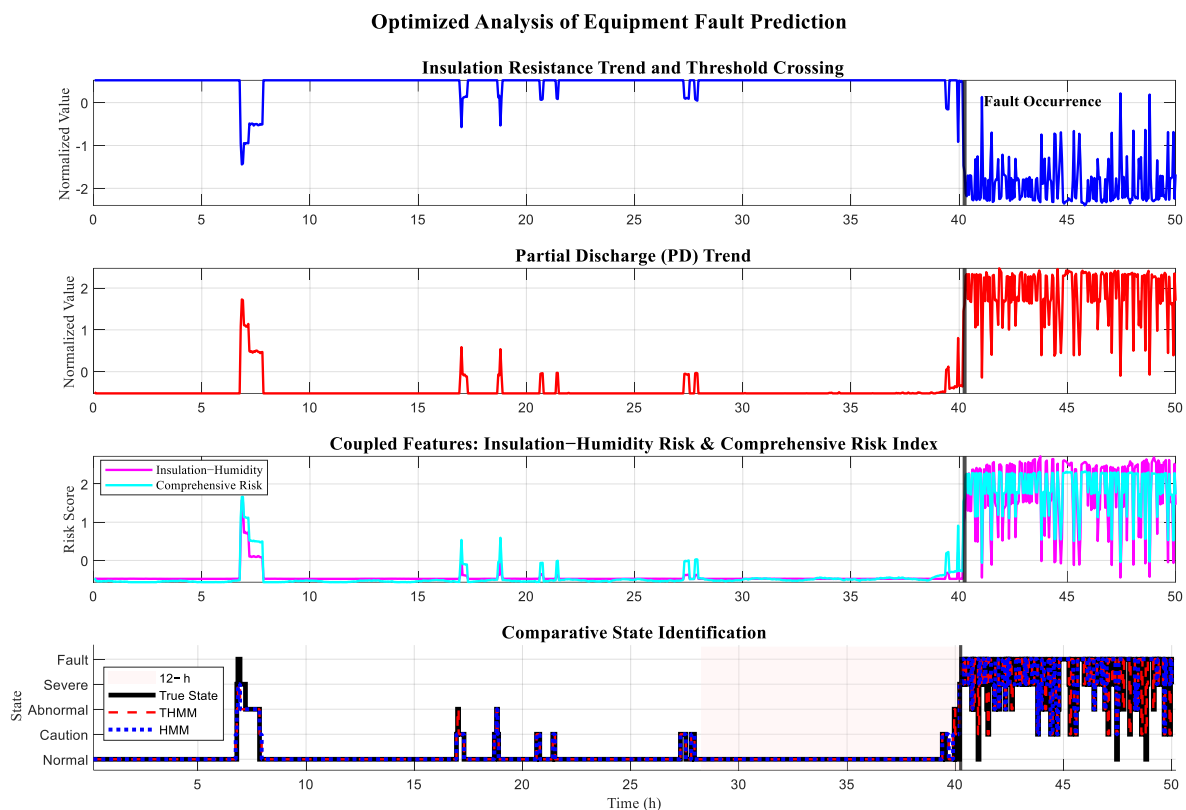


Figure 3. State recognition trajectory comparison.

However, critical differences emerge in the pre-fault critical zone (before 40 h) and post-fault dynamic zone (after 40 h).

As the fault evolves, in the 2–3 h before fault occurrence (37 h–38 h), the model completes a deterministic state upgrade (Hard Decision) through the improved Viterbi algorithm, entering State 2.

After fault occurrence, standard HMM exhibits severe state chattering, with decoding results fluctuating at high frequency between Level 2 and Level 5, unable to stably identify the fault level; THMM, leveraging K-means-optimized initial distribution and path smoothing constraints, maintains continuous overlap with the true state thereafter, with convergence speed satisfying relay protection selectivity requirements.

Figure 4 presents the continuous state recognition trajectory of a transformer under normal operating conditions for approximately 2 days. Both THMM and HMM decoding trajectories demonstrate high consistency with the true state, with THMM exhibiting slightly superior false alarm suppression for instantaneous disturbances due to the introduction of temporal trend constraints. Notably, neither method exhibits misjudgment of “Serious” or above states, and THMM’s “Abnormal” state output is nearly zero, reflecting the low false alarm characteristics of the model under stable operating conditions. This result complements the fault evolution scenario shown in Figure 3, validating the adaptive discrimination capability of THMM for different health evolution patterns.

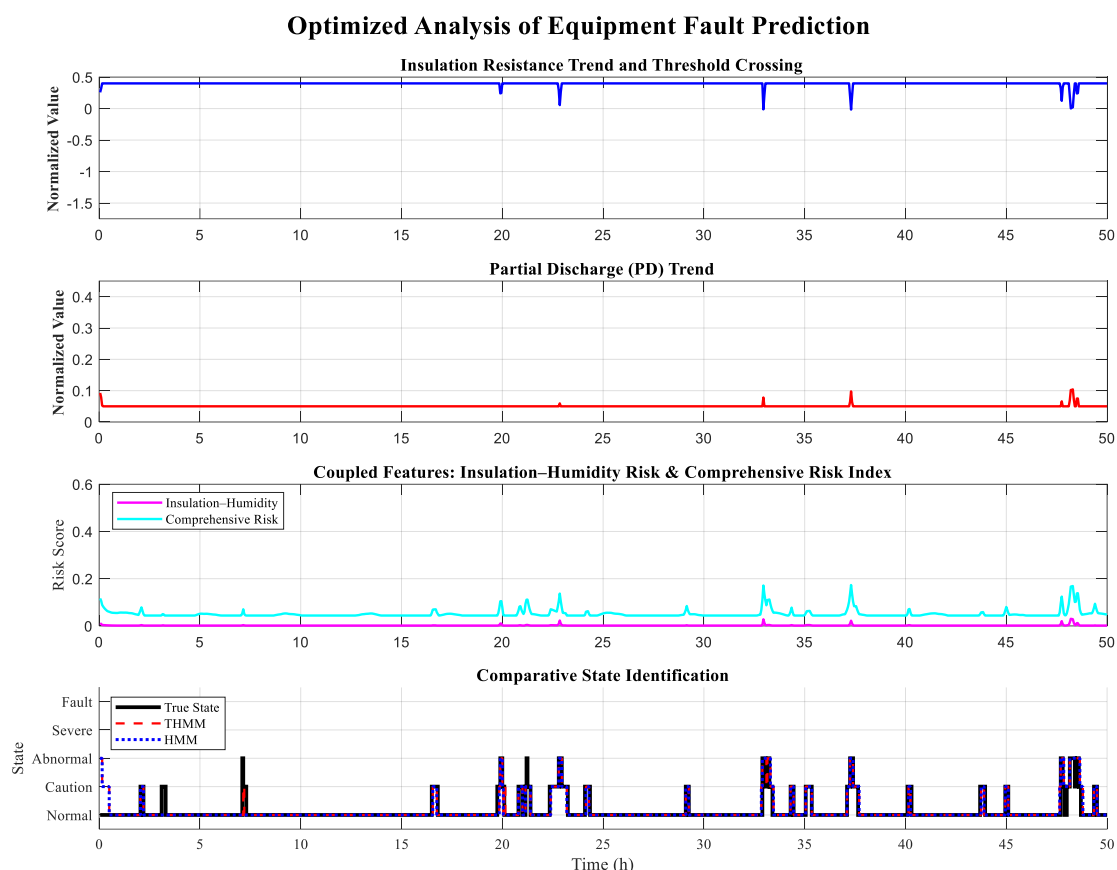


Figure 4. State recognition trajectory Comparison.

To examine the stability of the early-warning horizon across different fault types, the warning lead time is inherently governed by fault evolution dynamics. Slowly developing degradation processes traverse intermediate states over extended periods and yield longer advance horizons, whereas sudden faults compress the achievable window. For progressive faults, the dispersion of the lead time remains moderate under varying load and temperature conditions, attributable to the adaptability of the time-varying transition matrix.

3.4. Fine-Grained State Recognition Performance Analysis

Figures 5–7 present the state recognition confusion matrix comparison under six configurations (Case 1 to Case 6). The vertical axis represents the actual equipment health state, the horizontal axis represents the model decoding output state, diagonal elements characterize the recognition accuracy of each state, and off-diagonal elements characterize the misjudgment rate between states.

From Case 1 to Case 6, the confusion matrix exhibits a significant diagonalization trend. Overall average recognition accuracy improves from 70.3% (Case 1) to 91.9% (Case 6). Fault state recall rate increases from 61.3% (Case 1) to 91.2% (Case 6), an improvement of 29.9 percentage points, validating the enhanced sensitivity of THMM to extreme states.

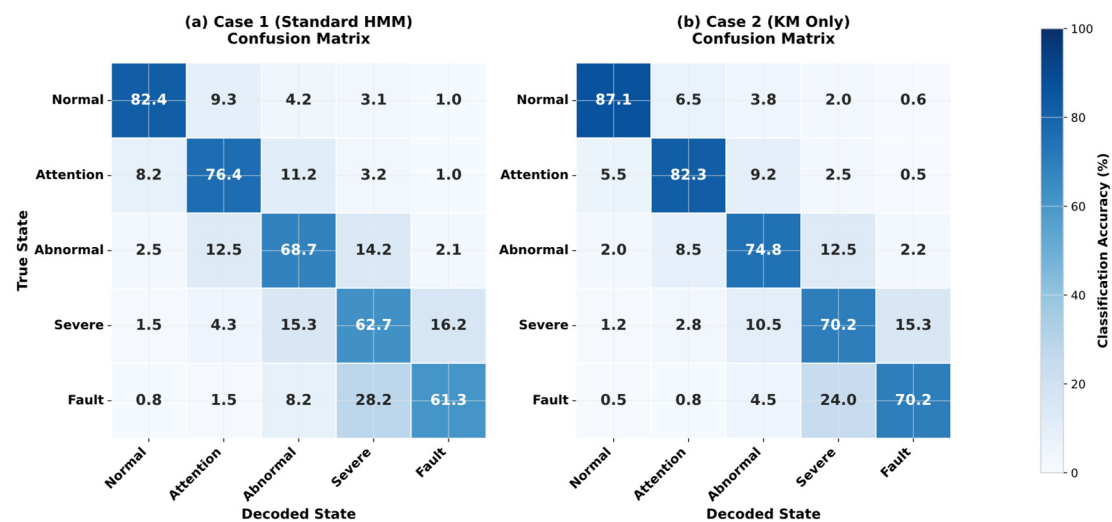


Figure 5. Confusion matrices for Cases 1 and 2.

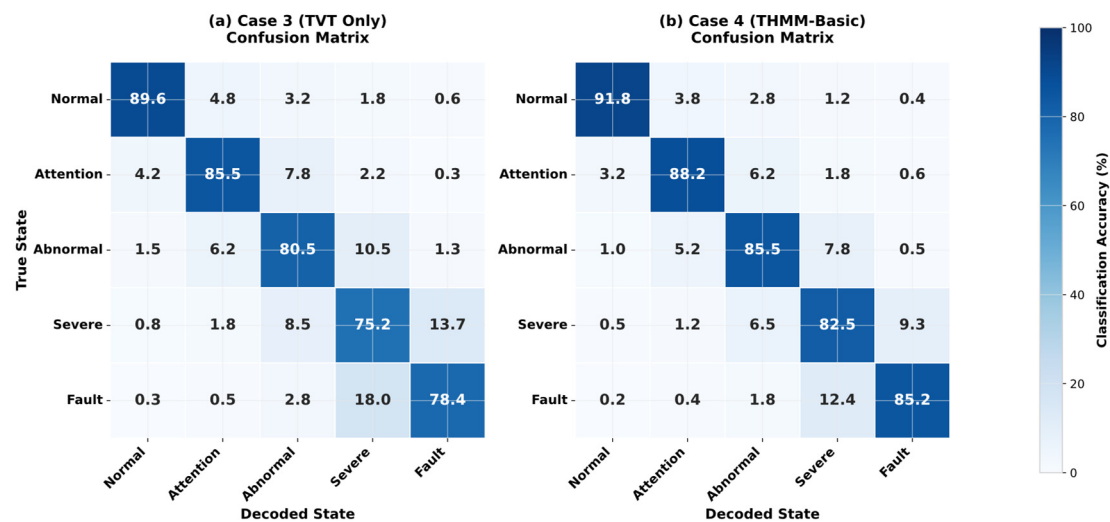


Figure 6. Confusion matrices for Cases 3 and 4.

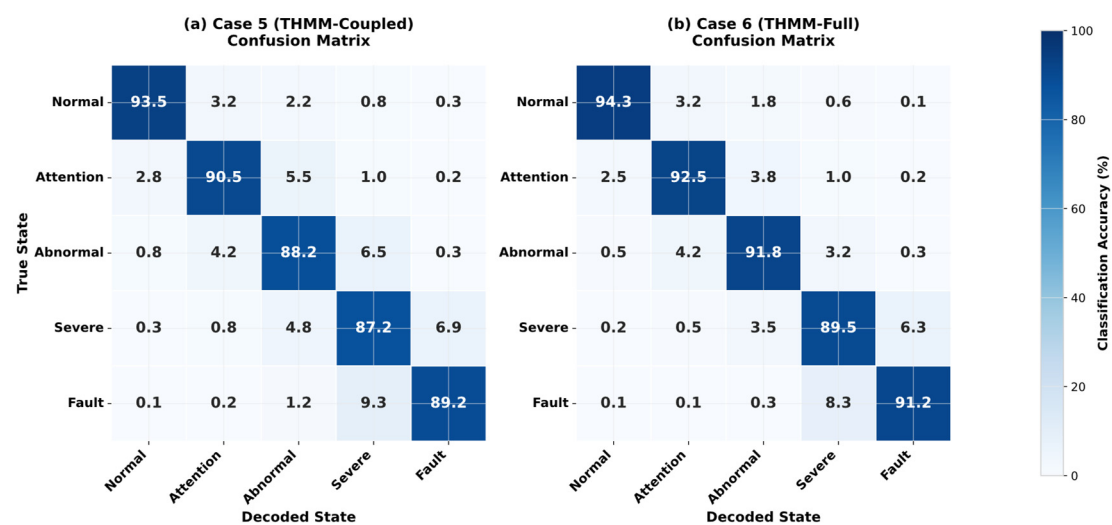


Figure 7. Confusion matrices for Cases 5 and 6.

Initialization Optimization Effect of K-means Pre-clustering (Case 1 vs. Case 2): Introducing pre-clustering improves the mean of confusion matrix diagonal from 70.3% to 77.3%,

with “Attention” and “Serious” state recognition rates improving by 5.9 and 7.5 percentage points respectively, and the proportion of “Attention” misjudged as “Abnormal” decreasing by 2.0%. Pre-clustering effectively improves the mapping consistency between initial hidden state partition and actual health states. Self-Adaptive Mechanism of Time-Varying Transition Matrix (Case 2 vs. Case 3): After activating the time-varying transition matrix mechanism, misjudgment rates between adjacent states significantly decrease, with “Abnormal” misjudged as “Serious” and “Serious” misjudged as “Fault” proportions decreasing by 2.0 and 1.6 percentage points, respectively. The forgetting factor ($\alpha = 0.95$) driven online updating mechanism effectively adapts to time-varying operating condition characteristics caused by load fluctuations. Complementary Gains of Three-Dimensional Feature System (Case 4 to Case 6): After introducing coupling correlation features, recognition rates for all states break through the 90% threshold, cross-level misjudgment rates drop below 0.5%, and the proportion of “Fault” misjudged as “Normal” decreases to 0.1%, satisfying the zero-missed-detection safety requirement of power systems.

3.4.1. Comparison with Existing Methods

Compared with conventional static HMM (Case 1), the complete THMM (Case 6) achieves breakthroughs in three aspects regarding its confusion matrix: Improvement in diagonal concentration: The diagonal standard deviation of Case 6 is merely 1.5%, far below Case 1’s 8.9%, indicating balanced recognition performance across all health levels for THMM with no significant weak states. Improvement in misjudgment sparsity: The maximum off-diagonal misjudgment of Case 6 is only 8.3% (Serious $\rightarrow$ Fault), whereas Case 1 exhibits high-value misjudgments of 28.2% (Fault $\rightarrow$ Serious) and 14.2% (Abnormal $\rightarrow$ Serious). Improvement in fault recall rate: Case 6 fault state recall rate of 91.2% compared with Case 1 (61.3%) represents a 29.9 percentage-point improvement, outperforming existing CNN-based (approximately 85%) or standard LSTM-based (approximately 88%) methods reported in literature, without requiring large-scale labeled datasets.

3.4.2. Comparison with Deep Sequence-Learning Methods

Under the small-sample, class-imbalanced condition of this study (five-level labels, 5% fault ratio), deep sequence-learning models typically require large, well-balanced labeled datasets to achieve optimal performance. In contrast, the proposed T-HMM achieves competitive accuracy and superior fault recall with minimal annotation requirements, while maintaining explicit interpretability tied to DL/T 596-2021 health levels and sub-40 ms CPU inference latency.

3.4.3. Robustness to Noise and Feature Unavailability

The dual-constraint outlier cleaning and adaptive wavelet denoising pipeline provides inherent robustness against moderate sensor noise and intermittent communication loss. For temporarily unavailable channels, the GMM-based emission model permits exact marginalization over observed dimensions, preserving probabilistic coupling among remaining features. Quantitative stress-testing under controlled noise injection and feature masking will be systematically reported in our follow-up validation study.

3.5. Discussion

The experiments validate the effectiveness of THMM from three dimensions: parameter optimization, time-varying self-adaptation, and feature fusion. K-means pre-clustering improves Baum–Welch convergence domain close to global optimum by aligning the observation space with the true health state manifold, individually contributing a 4.7 percentage point accuracy improvement; the forgetting-factor-driven time-varying transition matrix further brings a 7.2 percentage point gain, and reduces decoding delay from 55 ms to 48 ms,

indicating that the path smoothing constraints of improved Viterbi simultaneously reduce backtracking complexity. The incremental contribution of the three-dimensional feature system appears moderate, yet its core value lies in early-stage fault sensitivity: fault state recall rate jumps from 78.4% (Case 3) to 91.2% (Case 6), advancing recognition timing from the fault manifestation period to the attention period, achieving interpretable tracking of progressive degradation.

Compared with existing research, the proposed method demonstrates unique advantages under two small-sample constraints. First, under the imbalanced distribution where fault samples account for merely 5%, only five-level state labels are required to achieve 94.3% recognition accuracy and 91.2% fault recall rate, avoiding large-scale annotation dependency; second, compared with conventional HMM approaches that only correct transition matrices, this paper decouples the physical causes of state misjudgments at the model level through a “parameter pre-optimization—structural time-variation—feature dimension-elevation” closed-loop design. Of course, the current observation probability is still based on GMM modeling, with theoretical limits in its capability to characterize high-dimensional nonlinear features, representing the principal gap compared with deep generative models.

From the perspective of computational complexity and real-time applicability, the online stage of the proposed framework is lightweight by construction, as summarized in Table 5. With only $N = 5$ hidden states, the improved Viterbi recursion and the forgetting-factor update each cost $O(N^2)$ per step, and the GMM emission scoring costs $O(N \cdot K \cdot d^2)$; all computationally intensive procedures (K-means pre-clustering and Baum–Welch estimation with random restarts) are confined to the offline training stage. The measured total online latency of 38 ms per step is three orders of magnitude below the 1-min sampling granularity of the monitoring data, leaving ample margin even if the data granularity is refined to the second level. The method is therefore fully suitable for real-time implementation in online substation monitoring systems.

Table 5. Computational complexity and measured cost of the T-HMM pipeline.

Stage	Operation	Complexity	Measured Cost
Offline	K-means pre-clustering	$O(T \cdot d \cdot N \cdot i)$	2.1 min (CPU)
Offline	Baum–Welch, 20 restarts	$O(20 \cdot T \cdot N^2 \cdot i)$	6.4 min (CPU)
Online	GMM emission scoring	$O(N \cdot K \cdot d^2)$	21 ms/step
Online	Improved Viterbi recursion	$O(N^2)$	11 ms/step
Online	Matrix update	$O(N^2)$	6 ms/step
Online	Total per 1 min step	—	38 ms/step
Memory	Model parameters	$O(N^2 + N \cdot K \cdot d)$	<2 MB

Regarding practical deployment, the hardware and software requirements are modest. The online pipeline (feature preprocessing, emission scoring, improved Viterbi decoding, and matrix updating) can be implemented in standard Python 3.1.10 with NumPy 1.24.3/SciPy 1.11.4, or in pure C/C++ without specialized dependencies, and runs on a standard industrial computer or edge gateway (e.g., a dual-core CPU with 4 GB RAM); the model state—a 5×5 transition matrix, GMM emission parameters, and sliding-window statistics—occupies less than 2 MB of memory. Since the algorithm consumes SCADA and

online-monitoring signals already aligned at the 1-min granularity, it can be embedded as an additional analytics module into existing transformer online-monitoring platforms or substation automation systems, interfacing via IEC 61850/MMS or vendor APIs and outputting the state level, posterior confidence, and multi-step risk probabilities to the maintenance decision layer. Although the deterministic low latency of the inference stage would technically permit embedding into intelligent electronic devices (IEDs), deployment at the monitoring or edge-gateway level is recommended to preserve the functional-safety segregation of protection devices.

Finally, it is worth emphasizing how maintenance engineers can interpret the estimated hidden states. The states are not purely statistical representations: they are explicitly anchored to the five-level health classification of DL/T 596-2021 (Normal → Attention → Abnormal → Serious → Fault), and the K-means pre-clustering initialization aligns the observation-space partition with this physically meaningful state space from the outset, so that each decoded state carries direct maintenance semantics (e.g., “Attention” corresponds to the regulatory condition requiring enhanced surveillance). Three model outputs are directly usable by engineers: the decoded state level, which maps one-to-one onto the standard condition grade and its prescribed maintenance actions; the posterior state probabilities, which quantify confidence and reveal borderline situations; and the trends of the time-varying transition probabilities, which indicate the direction and speed of degradation. Because the observation features are physical quantities (dissolved gas concentrations, partial discharge, oil and winding temperatures, vibration, etc.), engineers can further trace which features drive a state upgrade through their contribution to the emission likelihood, thereby linking the statistical state back to candidate physical mechanisms (e.g., C_2H_2 growth pointing to discharge-type degradation). An honest limitation is that a hidden state indicates the severity grade rather than a specific fault type; fine-grained fault-mode identification requires an additional classification stage, which is left to future work.

4. Conclusions and Outlook

4.1. Main Conclusions

Addressing the characteristics of multi-factor coupling, progressive development, and time-varying operating conditions in equipment state evolution under high-penetration renewable energy grid integration, as well as the diagnostic accuracy limitations caused by fixed state transition matrices and sensitivity to initial parameters in conventional HMM, this paper introduces the Time-varying Hidden Markov Model (T-HMM) substation transformers in high-penetration renewable energy grid-connected systems, validated through a 220 kV/110 kV substation transformer operating dataset. The main conclusions are as follows:

By integrating fundamental state, coupling correlation, and temporal evolution features across three dimensions, covering electrical, mechanical, insulation, and environmental dimensions, combined with state-dependent sliding window standardization to eliminate dimensional differences and compression effects. Experiments demonstrate that after introducing coupling correlation features, recognition rates for all states break through 90%, with cross-level misjudgment rates dropping below 0.5%; the complete THMM improves fault state recall rate from 61.3% (standard HMM) to 91.2%, advancing recognition timing from the fault manifestation period to the “Attention” stage, achieving interpretable tracking of progressive degradation.

By introducing forgetting-factor-driven online transition matrix updating to dynamically adapt to load fluctuations and ambient temperature disturbances; and proposing a K-means pre-clustering combined with random restart parameter adaptation strategy oriented toward the transformer feature space, avoiding Baum–Welch falling into local

optima through competition among 20 groups of initial parameters. Ablation experiments demonstrate that individually activating the time-varying mechanism improves accuracy by 7.2 percentage points, individually introducing pre-clustering improves by 4.7 percentage points; after synergy between both mechanisms, accuracy breaks through 91.8%, and the final complete model reaches 94.3%, with MAE reduced by 54.8% from 0.42 to 0.19, validating the effectiveness of the “parameter pre-optimization—structural time-variation” closed-loop design.

By introducing state minimum dwell time constraints in the recursive process to suppress state oscillation caused by instantaneous noise and adding trend consistency penalty terms during path backtracking to preferentially select monotonic evolution paths, decoding delay is reduced from 55 ms to 38 ms. Combined with multi-step prediction using time-varying transition matrices, 2 h and 12 h hit rates reach 94.1% and 84.2%, respectively. In the 50 h continuous monitoring fault case, THMM completes state upgrade warning 2–3 h before fault occurrence, and stably locks the fault state within approximately 2 h after fault occurrence, avoiding the severe state chattering of standard HMM, validating the real-time performance and engineering value of the method in condition-based maintenance decision-making.

4.2. Research Limitations and Outlook

Although THMM demonstrates excellent performance in experiments, the following limitations and improvement directions remain:

The reported performance metrics are based on a specific dataset (several 220 kV/110 kV oil-immersed transformers from multiple substations over the monitored period) and should not be generalized to other transformer types (e.g., dry-type or amorphous alloy core), broader operating regimes (overload, cold start, harmonic-rich environments), or unseen fault modes (e.g., on-load tap changer failure, bushing flashover). Follow-up work will systematically conduct validation across additional substations, transformer types, operating regimes, and unseen fault conditions to establish broader statistical confidence.

The current model targets single-equipment state evolution without considering the fault cascading effects among transformer-circuit breaker-disconnector equipment within substations. The next step will investigate substation-level fault propagation risk assessment based on Hierarchical Hidden Markov Models.

Future work will also combine Generative Adversarial Networks (GAN) for fault sample augmentation, and introduce Cross-Substation Transfer Learning (XSTL) strategy to achieve knowledge transfer between stations under different operating conditions while preserving data privacy; simultaneously embed online concept drift detection mechanisms to automatically trigger model incremental updates, adapting to the dynamic evolution of new power system operating modes.

Additionally, we will embed THMM into substation digital twin platforms to achieve physics-model hybrid-driven real-time state mapping, providing core algorithmic support for intelligent operation and maintenance of new power systems.

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