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Risk Estimation of Oil and Gas Industry Equipment

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ABSTRACT
The oil and gas industry is an essential part of the global energy supply. Offshore exploration and production are important. In drilling, both onshore and offshore, the Bottom Hole Assembly (BHA) plays a crucial role. Logging While Drilling (LWD) tools depend on electronic boards that are very sensitive to downhole conditions like high pressure, vibration, and temperature changes. When these boards fail, it can disrupt operations, increase costs, and affect safety. Traditional maintenance methods struggle because they can't respond to changing risk conditions. This study creates a probabilistic framework using the Hidden Markov Model (HMM) to estimate the failure risk of LWD electronic boards. The research uses operational data, including temperature, pressure, vibration severity, usage, and fault records as observation sequences. The model is trained with the Baum-Welch algorithm, which helps identify hidden degradation states and generate time-varying failure probabilities. Results are divided into four risk levels: low, moderate, high, and extreme. This classification provides a clear risk profile for proactive monitoring. The findings indicate that HMM effectively captures degradation transitions. It also offers early warnings and improves the reliability assessment of LWD tools, potentially benefiting offshore asset integrity management.

Keywords: *Hidden Markov Model, Logging While Drilling, Offshore Drilling, Risk Assessment*

1. INTRODUCTION
The oil and gas industry is a key part of global energy supply [1], with offshore drilling playing a vital role in exploration and production [2]. In these operations, the reliability of downhole equipment is crucial for safety, efficiency, and cost savings. Among these tools, Logging While Drilling (LWD) systems are particularly important as part of the Bottom Hole Assembly (BHA) [2]. They provide real-time downhole measurements that aid decision-making and improve drilling performance [2].

Despite their significance, as noted by reliability engineer of oil and gas service, LWD tools face tough conditions like high pressure, varying temperatures, vibration, and mechanical shock. These harsh environments often lead to unexpected failures of electronic boards. Such failures can disrupt operations, raise maintenance costs, and reduce drilling efficiency [3]. Traditional maintenance methods, like preventive schedules or corrective repairs are limited effectiveness. Preventive strategies can lead to unnecessary interventions and costs, while corrective actions only tackle issues after failures happen. These limitations highlight the need for advanced maintenance strategies that can dynamically estimate failure risks.

In recent years, researchers have looked into different ways to improve the reliability of downhole electronics [4]. They have developed probabilistic models to estimate the probability of failure and applied machine learning to predict failures using operational data. Despite these advances, using HMMs for real-time risk estimation of LWD electronic boards is still not well explored. Most existing methods either depend only on historical data or do not adjust well to changing operating conditions. They rarely provide continuously evolving risk levels.

This study addresses these gaps by proposing a probabilistic risk estimation framework using the Hidden Markov Model (HMM). The HMM is applied to operational data, including temperature, pressure, vibration severity, usage history, and fault records to uncover hidden degradation states and compute time-varying probabilities of failure. The resulting probabilities are classified into four levels, low, moderate, high, and extreme, providing a structured and interpretable risk profile of electronic board health.

The objective of this research is to develop a systematic model for estimating the failure risk of LWD electronic boards in real time. By capturing dynamic changes in risk levels, the proposed method enhances reliability assessment and supports proactive monitoring of critical downhole equipment in offshore drilling operations.

2. METHODOLOGY

2.1 Research Approach
This study develops a probabilistic framework based on the Hidden Markov Model (HMM) to estimate failure risk of Logging While Drilling (LWD) electronic boards. The

HMM is trained using operational data and then applied to infer hidden degradation states and dynamic probabilities of failure. The methodology refers to Figure.1.

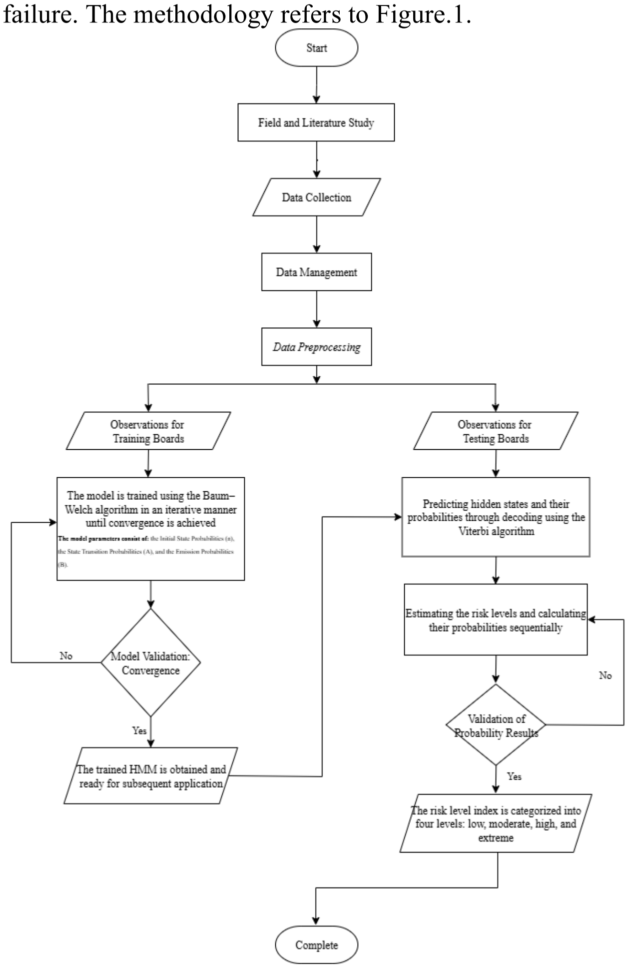

Figure 1. Methodology Diagram

2.2. Data Preparation

The data used in this study were collected from operational records of Logging While Drilling (LWD) tools. The dataset (acquired from electronic boards with Part Number 10068098) includes variables influencing electronic reliability such as maximum temperature (℃), downhole pressure (Mpa), vibration severity (hr), usage history (hour), and recorded faults (x).

Table 1. Sensor Data (without VSS)

No	SN	*Temp*	*Press*	*Fault Hist*	*Life-time*
1	11719435	98.3	52.52	0	94
2	11719435	85	15.53	0	135
3	11719435	116.7	34.86	0	79
4	11719435	46.1	5.1	1	70
5	11747011	131	28.75	0	30
⋮	⋮	⋮	⋮	⋮	⋮
2286	T065091002C	106.1	116.09	1	136

Table 2. Sensor Data (VSS)

No	*Serial Number*	VSS Lateral Level 1-7 (gRMS)						
		1	2	3	4	5	6	7
1	11719435	32.57	9.94	0.9	0.12	0	0	0
2	11719435	4.17	17.92	0.53	0.03	0.01	0	0
3	11719435	53.92	67.2	1.77	0.23	0	0	0
4	11719435	0.74	0.28	0.04	0	0	0	0
5	11747011	0.14	28.09	0.01	0	0	0	0
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
2286	T06509 1002C	101.04	4.62	0.23	0.01	0	0	0

After preprocessing (cleaning, normalization, and outlier handling), the data are structured into observation sequences O={o$_1$,o$_2$, …, o$_T$}, where each observation corresponds to the condition of the electronic board at time step *t*.

2.3. Hidden Markov Model

The HMM is defined by a set of parameters, λ= (π, A, B), which govern its behavior [5]. These parameters must be initialized before the training process begins.

- *Initial State Distribution (π):* vector where π_i is the probability of the system being in a specific hidden state S_i at the initial time step $t=1$. This can be written as:

$$\sum_{i=1}^{N} \pi = 1 \tag{1}$$

$$\pi = [\pi_1, \pi_2, \pi_3, \pi_4] \tag{2}$$

For this study, the hidden states correspond to different operational health conditions of the electronic board, such as "low" "moderate" "high" and "extreme". The π vector is initialized with random values and then normalized so that the sum of its elements equals one.

- *State Transition Matrix (A):* an $N \times N$ matrix, where N is the number of defined hidden states. Each element a_{ij} represent the probability of transitioning from state S_i to state S_j between consecutive time steps. In this study, four hidden states are used—*low, moderate, high,* and *extreme*, forming a 4×4 transition matrix. Each row must sum to 1:

$$\sum_{j=1}^{N} a_{ij} = 1 \tag{3}$$

$$a_{ij} = P\left(q_{t+1} = S_j \,\middle|\, q_t = S_i\right) \tag{4}$$

The matrix is initialized with random values, with each row summing to one to ensure a valid probability distribution for all possible state transitions.

- *Emission Probabilities (B):* The emission probability matrix B represents the likelihood of observing a specific feature vector given a hidden state. For continuous observations, B is modeled using a multivariate Gaussian distribution parameterized by the mean vector (μ) and covariance matrix (Σ) of each hidden state. The emission probability for a given observation o_t in state S_i is expressed as:

$$b_j\, O_t = \frac{1}{\sqrt{(2\,\pi)^D |\Sigma_j|}} exp\left(-\frac{1}{2}(O_t - \mu_j)^T \Sigma_j^{-1(O_t - \mu_j}\right. \quad (5)$$

Where D is the number of observation features, μ_i is the mean vector, and Σ_i is the covariance matrix corresponding to the i^{th} hidden state. In this study, four hidden states (*low, moderate, high,* and *extreme*) and five observation features (maximum temperature, pressure, vibration duration, fault history, and usage hours) are defined. This formulation allows the HMM to capture the statistical behaviour of each degradation state and relate sensor-based observations to the underlying reliability condition of the electronic boards.

2.4. HMM Training Algorithm

The Baum-Welch algorithm is an iterative Expectation-Maximization (EM) algorithm used to find the optimal HMM parameters λ that maximize the likelihood of the observed data.

2.4.1. Expectation Step (E-Step)

This step computes the forward and backward probabilities to derive the expected number of transitions and state occupations.

- *Forward Probability (α):* The probability of observing the sequence O_1, ..., O_t and ending in state S_i at time *t*.
  - *Initialization*:

$$\alpha_t(i) = \pi_i \cdot b_i \cdot (O_1) \quad (6)$$

  - *Recursion:*

$$A_t(j) = \left[\sum_{i=1}^{N} A_{t-1}(i) \cdot A_{ij}\right] \cdot B_j(O_t) \quad (7)$$

  - *Scaling:*

$$c_t = \sum_{j=1}^{N} A_t(j) \quad (8)$$

$$Atnewj{=}At(j)ct \quad (9)$$

- *Backward Probability (β):* The probability of generating the remaining sequence of observations $O_{t+1},\ldots,O_T$ from state S_i at time *t*.
  - *Initialization*:

$$B_T(i) = 1 \quad (10)$$

  - *Recursion:*

$$B_t(i) = \sum_{j=1}^{N} A_{ij} \cdot B_j(O_{t+1}) \cdot \beta_{t+1}(j) \quad (11)$$

  - *Scaling:*

$$\beta_t^{new}(i) = \frac{\beta_t(i)}{c_t} \quad (12)$$

- *State Probabilities*

- *Gamma (γt(i)):* The probability of being in state S_i at time *t*, given the entire observation sequence. It is derived from the forward and backward probabilities:

$$\xi_t(i,j) = \frac{\alpha_t(i)\cdot A_{ij}\cdot B_j(O_{t+1})\cdot \beta_{t+1}(j)}{\sum_{i=1}^{N}\sum_{j=1}^{N} \alpha_t(i)\cdot A_{ij}\cdot B_j(O_{t+1})\cdot \beta_{t+1}(j)} \quad (13)$$

- *Xi (ξt(i,j)):* The probability of transitioning from state S_i at time *t* to state S_j at time t+1, given the entire observation sequence:

$$\gamma_t(i) = \sum_{j=1}^{N} \xi_t\,(i,j) = \frac{\alpha_t(i)\cdot \beta_t(i)}{\sum_{j=1}^{N} \alpha_t(j)\cdot \beta_t(j)} \quad (14)$$

2.4.2. Maximization Step (M-Step)

This step updates the HMM parameters using the probabilities computed in the E-step

- *Updated Initial State Distribution:*

$$\hat{\pi}_i = \gamma_1(i) \quad (15)$$

- *Updated State Transition Matrix:*

$$\hat{\alpha}_{ij} = \frac{\sum_{t=1}^{T-1} \xi_t(i,j)}{\sum_{t=1}^{T-1} \gamma_t(i)} \quad (16)$$

- *Updated Emission Parameters (Mean and Covariance):*
  Mean

$$\hat{\mu}_k = \frac{\sum_{t=1}^{T} \gamma_t(k) O_t}{\sum_{t=1}^{T} \gamma_t(k)} \quad (17)$$

Kovarian

$$\frac{\sum_{t=1}^{T} \gamma_t(k)(O_t - \hat{\mu}_k)^T}{\sum_{t=1}^{T} \gamma_t(k)} \quad (18)$$

2.5. Decoding

Decoding is the main process used to utilize a trained HMM model. This stage employs the Viterbi Algorithm to find the most probable sequence of hidden states that generate the observed sequence. This algorithm comprises three main steps: initialization, recursion, and backtracking.

- *Initialization:*

$$V_1(j) = \pi_j \cdot b_j(o_1) \quad (19)$$

- *Recursion:*

$$V_t(j) = max_i(V_{t-1}(i) \cdot a_{ij}) \cdot b_j(o_t) \quad (20)$$

$$P_t(j) = arg\ max_i\left(V_{t-1}(i) \cdot a_{ij}\right) \quad (21)$$

- *Backtracking:*

$$\hat{q}_T = \arg max_j(V_T(j)) \quad (22)$$

$$\hat{q}_t = P_{t+1}(\hat{q}_{t+1}) \quad (23)$$

2.6. Risk Level Estimation

Risk level estimation is the process of converting the sequence of hidden states into a measurable and easily understandable risk metric. This stage aims to quantify risk by classifying the equipment's condition into clear risk categories, such as low, moderate, high, or extreme. Furthermore, this stage supports decision-making by providing information that can be utilized by the decision support system to determine the most appropriate maintenance strategy. The steps involved are state mapping, interpretation, and subsequent risk probability calculation.

- *State* Mapping: Each hidden state defined at the beginning of the modeling process is mapped directly to a risk category based on the IEEE framework.

Table 3. State to Risk Level Mapping

Board Condition (HMM Output)	Description	Relevance to IEEE 1856-2017
Low	Operating under optimal conditions	Meets the reliability standards required for Tier ¾ (or Level ¾)
Moderate	Beginning to show signs of degradation	Still within acceptable limits, but approaching the lower bound of Tier ¾ (or Level ¾)
High	Significant degradation; probability of failure is increasing	No longer meets the reliability standards required by Tier ¾ (or Level ¾); immediate action is necessary
Extreme	Failure is almost certain	Far beyond the safety limits of Tier ¾ (or Level ¾); operational failure is unavoidable

- *Interpretation*: The decoding results from the Viterbi algorithm, which yield the sequence of hidden states, are analyzed to observe trends in risk change.
- *Subsequent Risk Probability Calculation*: Although Viterbi yields the single most likely state sequence (path), additional information can be obtained through the posterior probabilities from the Forward-Backward algorithm. This allows for the calculation of the probability that the system is at each risk level at any given time.

3. RESULTS AND DISCUSSIONS

3.1 Sensor Data Analysis

The data utilized in this study were obtained from sensor recordings on a LWD tool during field drilling operations. The observed parameters include temperature (°C), pressure (PSI), and lateral vibration (gRMS), which are categorized into seven measurement levels (1-7) over a specific time duration (hour). These three parameters represent the operational environment conditions that directly influence the reliability of the tool's electronic board.

Table 4. Sensor Data Statistics as Model Input

Parameter	Unit	Min	Max	Mean	Std. Dev
Temperature	℃	10	154	81	31
Lateral Vibration Lv 1	hr	0.01	288.71	12.48	19.82
Lateral Vibration Lv 2	hr	0.01	360.06	32.78	39.54
Lateral Vibration Lv 3	hr	0.01	179.31	4.36	11.56
Lateral Vibration Lv 4	hr	0.01	90.63	0.80	3.98
Lateral Vibration Lv 5	hr	0.01	32.7	0.11	1.03
Lateral Vibration Lv 6	hr	0.01	7.66	0.02	0.21
Lateral Vibration Lv 7	hr	0.01	1.32	0.0	0.05
Pressure	psi	461	23,643	3,393	3,441

Based on the equipment specifications, the maximum allowable temperature is 150 °C. Therefore, the recorded maximum value of 154 °C indicates a condition that exceeds the design limit, potentially leading to the chemical degradation of the circuit's protective layer, accelerated component aging, and an increased failure rate of the electronic board. This wide temperature range suggests that the tool operates under highly variable and thermally challenging environmental conditions.

3.2 Hidden Markov Model (HMM) Modeling

This stage aims to estimate the hidden states of the LWD tool's electronic board based on observed data of temperature, pressure, and vibration exposure duration. The HMM was selected due to its capability to dynamically capture changes in the tool's reliability status within a time-dependent stochastic system, by accounting for both inter-state transition probabilities and emission probabilities of the observation variables.

3.2.1. Model Convergence Results

- **Model Parameters After Convergence**

After the iterative training process using the Baum–Welch algorithm reached a change tolerance criterion of 1×10^{-4}, the converged HMM parameters were obtained. The final parameters consist of three main components:

1. **Initial Probability Vector (π)**

$$\pi = [1 \quad 0 \quad 0 \quad 0] \qquad (24)$$

This value indicates that the system almost always initiates operation in the Low Risk condition (State 1), which aligns with the physical behavior of the LWD tool when it is first put into use, before being exposed to operational stress.

2. **Transition Matrix (A)**

$$A = \begin{bmatrix} 0.86778 & 0.1020 & 0.0226 & 0.0076 \\ 0.5129 & 0.4564 & 0.0275 & 0.0032 \\ 0.6085 & 0.0856 & 0.2922 & 0.0137 \\ 0.7074 & 0.1815 & 0 & 0.1111 \end{bmatrix} \qquad (25)$$

This matrix describes the pattern of transitions between risk states. The dominant diagonal values (0.8678, 0.4564, 0.2922, 0.1111) indicate that the system tends to persist in the same condition over multiple periods (persistence).

The system transitions more frequently from *Low* → *Moderate* and *Moderate* → *Low* compared to direct transitions to more extreme states. Direct transitions to Extreme Risk are very low (<1%), which is consistent with the reality that extreme conditions rarely occur without prolonged stress accumulation.

verall, this transition matrix pattern indicates that the model is capable of capturing the dynamics of a fluctuating operational risk cycle, although it is not yet constrained by a unidirectional degradation path. To achieve a more realistic representation of degradation, constraining the transition direction (left-to-right HMM) can be implemented in the next development phase.

3. *Mean Emission* (μ)

$$\mu = \begin{bmatrix} 0.008 & 0 & 0.0087 & 1.7896 & 0 \\ 0.0092 & 0 & 0.0415 & 5.1529 & 0 \\ 0.0083 & 0.002 & 0.0186 & 2.7979 & 0 \\ 0 & 0 & 0 & 0 & 0 \end{bmatrix} \quad (26)$$

The μ values represent the average sensor observations for each risk state. From these values, an increasing pattern in the main features can be observed. The mean pressure and lateral vibration increase significantly in the Moderate and High Risk states, indicating a heavier operating condition approaching the tool's design limits.

The Extreme state exhibits μ values approaching zero because the number of observation data points is very limited. This likely occurs because extreme conditions are rarely reached during normal operation, thus the emission distribution for this state is not yet fully represented.

The distributions across the states are sequential and do not significantly overlap, which demonstrates that the model is capable of distinguishing between each risk category based on the statistical patterns of the sensors.

4. *Covariance Emission* (Σ)

Σ is not explicitly displayed. This is because the model utilized employs the diagonal covariance assumption, where each observation feature is considered to be not directly correlated with the others.

Consequently, only the variances (the diagonal values of Σ) are updated during the training process, while the off-diagonal values are assumed to be zero. Furthermore, since the dataset has been normalized and the variance changes in each iteration were relatively small, the system only displays the parameters that underwent significant updates, namely the mean vector ($\hat{\mu}$) and the transition matrix ($\hat{A}$).

Although not displayed, the parameter is still accounted for in the calculation of the Gaussian Probability Density Function (PDF) at every iteration to estimate the model's log-likelihood value.

- ***Log-likelihood***

During the training process, the log-likelihood value gradually increased with the increasing number of iterations, indicating that the model parameters are becoming better suited to the data patterns. The obtained convergence curve shows a sharp increase in the initial iterations and stabilized after reaching its maximum value at the 20th iteration.

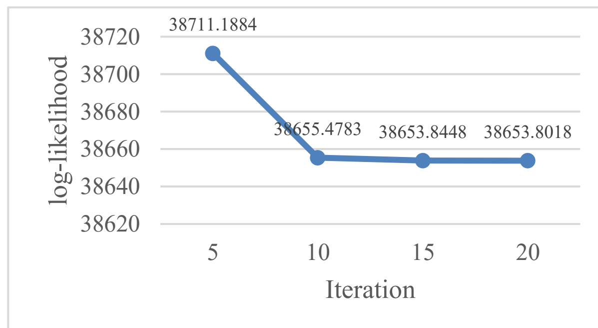

Figure 2. Log-likelihood per Iteration

From these results, it can be concluded that the model achieved convergence at the iteration, with a maximum log-likelihood of 38653.8 The stability of the log-likelihood value indicates that the optimization process has found the combination of parameters best suited to the training data, thus the model is considered numerically converged.

3.2.2. Results of Risk State Sequence Estimation

The decoding results using the Viterbi algorithm yield the risk state sequence for each observed Training Board. The following table presents two examples of decoding results for serial numbers 16171982 and 13157447.

Table 5. Decoding Results of the Tool with Serial Number 16171982

Step	P_1	P_2	P_3	P_4	Dominan State
t_1	0.986	0.0137	4×10^{-6}	0	*Low*
t_2	0.002	0.997	9×10^{-6}	0	*Moderate*
t_3	0	0	1.000	0	*High*

Table 6. Decoding Results of the Tool with Serial Number 13157447

Step	P_1	P_2	P_3	P_4	Dominan State
t_1	0.932	0.067	6×10^{-5}	0	*Low*
t_2	9×10^{-6}	0.999	4×10^{-5}	0	*Moderate*
t_3	4×10^{-11}	0.005	0.994	0	*High*

Both sequences display the state transition *Low* → *Moderate* → *High*, which illustrates a gradual and stable degradation process from a safe condition toward high risk. The absence of a status reversal (*High* → Low) after applying the additional pseudo correction on the codes indicates that the model successfully recognized the sequential degradation pattern and does not exhibit risk 'recovery' without a physical cause.

In the estimation results using the Viterbi algorithm, the model produced three time-steps (t_1, t_2, t_3) for the data of Serial Numbers 16171982 and 13157447. Each time step represents one observation period based on the available data. This number of time steps indicates that the observation data used for these devices consisted of three primary operational phases.

3.2.3. Analysis of Operational Parameter Changes on Risk Level

Table 7-8 illustrates the correlation between the change in risk level resulting from the HMM and the rate of change of operational variables across four devices (Serial Numbers 13157447, 14383815, 15127248, and 16171982).

Each column shows the range of change values for Temperature, Vibration, Pressure, Lifetime, and Fault History that occurred throughout the transition between risk levels.

Table 7. Correlation Between -Derived Risk Level Changes and the Rate of Change of Operational Variables for Risk, Temperature, and Pressure

Serial Number	Risk	Temp	Press
13157447	1 – 2 – 3	31,5 - 66,7 - 106,5	2280 – 21370 - 48380
14383815	1 – 1 – 1 – 2 – 2 – 2 – 3	81.5 – 84.2 – 91.6 – 103.5 – 58.1 – 76.1 – 97.6	1190 – 21030 – 20890 – 25510 – 19310 – 17580 – 19310
15127248	1 – 2 – 3	104.4 – 104.4 - 131	19580 – 24130 – 24130

Table 8. Correlation Between -Derived Risk Level Changes and the Rate of Change of Operational Variables for Lifetime, Usage, and VSS

Serial Number	Lifetime	Usage	VSS axial
13157447	1 – 2 – 3	31,5 - 66,7 - 106,5	2280 – 21370 - 48380
14383815	1 – 1 – 1 – 2 – 2 – 2 – 3	81.5 – 84.2 – 91.6 – 103.5 – 58.1 – 76.1 – 97.6	1190 – 21030 – 20890 – 25510 – 19310 – 17580 – 19310
15127248	1 – 2 – 3	104.4 – 104.4 - 131	19580 – 24130 – 24130

Across all four devices, the majority exhibit a pattern of progressive risk increase, for example 1–2–3 or 1–1–2-2-2–3. This indicates that the HMM identifies gradual degradation consistent with the phenomena of wear and tear and exposure to extreme environments typical of a downhole tool. The absence of illogical transitions (such as an extreme decline from 3 → 1), demonstrates model stability.

Based on the analysis results in the table above, it can be concluded that the pattern of change in operational variables has a trend that is consistent with the increase in risk levels. The HMM is capable of recognizing that increases in temperature and pressure are the primary indicators of degradation, while a decrease in Lifetime and an increase in Fault History serve as secondary symptoms that reinforce risk detection. Therefore, the model is proven effective in describing the relationship between actual sensor data and the tool's reliability level in both a temporal and physical context.

3.3. Visualization and Validation of Estimated Risk Levels

To verify that the risk classification provided by the HMM model aligns with the actual operational behavior, a visualization was performed on the main variables utilized as observation data. This visualization was conducted using data from Serial Number 16171982, which was also previously used in the risk state sequence analysis example (t_1–t_3).

The visualization was conducted by mapping the mean values of the sensor parameters (Temperature, Vibration, Pressure, Lifetime, and Fault History) against the Risk Level (1–3) generated by the HMM model at each time step. The visualization results can be seen in Figure 3 through 6 as follows.

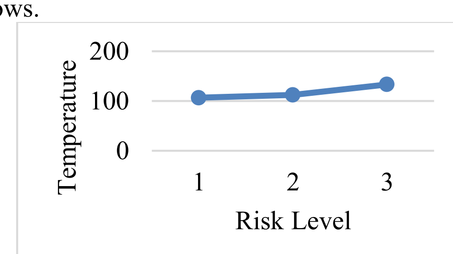

Figure 3. Risk Level Trend to Temperature

The temperature rises sharply from Risk Level 1 to Risk Level 3. This rise matches the physical traits of electronic systems, where higher operating temperatures speed up the wear and tear of components. This pattern shows that the HMM model connects the temperature increase with a higher risk level.

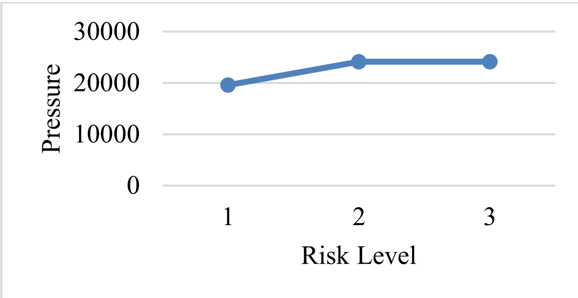

Figure 4. Risk Level Trend to Pressure

Pressure shows a significant increase when moving from Low to Moderate Risk. This suggests that it helps start early degradation. However, after reaching about 24,000 psi, the effect becomes stable. This indicates that pressure mainly acts as a trigger that enhances other environmental factors like temperature and vibration.

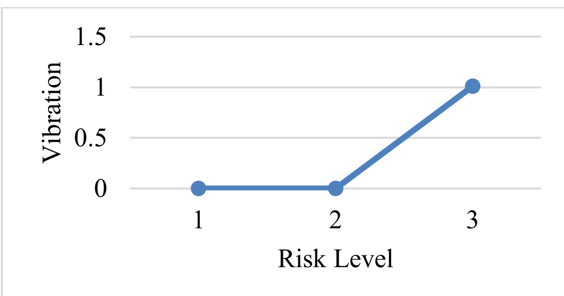

Figure 5. Risk Level Trend to Vibration

The rise in vibration, particularly in the *Extreme Risk Level*, indicates a threshold effect consistent with mechanical resonance behavior, where exceeding material vibration tolerance leads to a sudden increase in failure probability

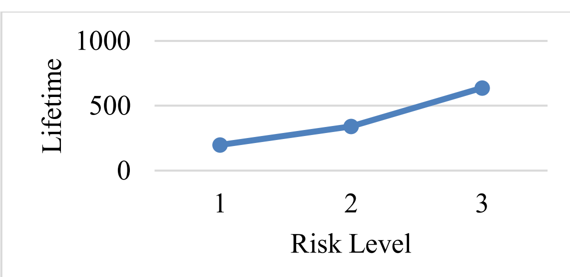

Figure 6. Risk Level Trend to Lifetime

The progressive increase in operational time (lifetime) across risk levels shows that the HMM effectively represents temporal reliability degradation. Higher risk probabilities at longer operation hours correspond to the wear-out phase, where failure rates increase due to accumulated thermal and vibrational stresses.

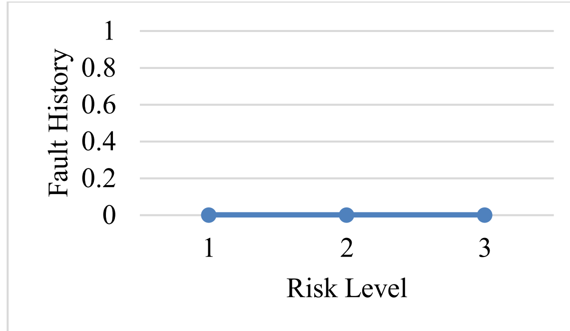

Figure 7. Risk Level Trend to Fault History

The fault history remains zero across all risk levels, confirming that the electronic board with this serial number has not yet experienced any recorded failures. This supports the interpretation that the increasing risk is driven purely by environmental and operational parameters rather than by prior fault events.

These results show that the relationship between operational parameters and HMM-estimated risk levels matches the physical behavior of LWD tools. Temperature, pressure, vibration, and operational time all increase as risk levels rise, while the fault history stays the same because there have been no previous failures. This indicates that the HMM gives reliable risk estimates rather than random ones. It follows a logical pattern of reliability decline that aligns with principles of reliability engineering. These findings support [6], which reported that in extreme environments, thermal cycling, vibration, and shock can cause micro-cracking and delamination in electronic components. In the same way, [7] discovered that high temperature and pressure can speed up failures in materials and electrical connections if thermo-mechanical stresses are not managed correctly.

3.4. Analysis of Risk State Distribution

In addition to performing risk state sequence estimation using the Viterbi algorithm, this study also analyzed the distribution of risk status classifications across all utilized Training Boards. This analysis aims to evaluate the proportion of degradation conditions for each device and to assess the model's consistency with realistic operational behavior.

Based on the Viterbi decoding results; the risk status distribution is obtained as follows:

Table 9. Quantity of Risk Status Distribution

Risk Level	Number of Devices	Percentage (%)	Interpretation
Level 1 *(Low Risk)*	502	63%	Stable condition; components operating normally

Level 2 *(Moderate Risk)*	236	30%	Beginning of risk escalation; initial degradation signs
Level 3 *(High Risk)*	43	5%	High risk; significantly reduced reliability
Level 4 *(Extreme Risk*)	17	2%	Critical condition; approaching tool design limits

The distribution above shows that most devices are in Risk Level 1 (Low Risk), indicating that most tools are still operating within safe limits. Only a small fraction of devices reaches Levels 3 and 4, suggesting that extreme conditions are rare occurrences that only happen to tools exposed to high temperature and pressure for prolonged periods.

Interestingly, the results also show that the model does not perform direct prediction to Risk Level 4 without any prior historical trace. This means the system does not suddenly classify a device as being in an *Extreme* condition, unless the tool has previously passed through the *Low → Moderate → High*. This indicates that the HMM model has successfully captured the degradation sequence logically and sequentially, consistent with the physical principle of electronic component failure, which is cumulative and non-spontaneous.

4. CONCLUSIONS

This study created a risk estimation framework using the Hidden Markov Model (HMM) to evaluate how Logging While Drilling (LWD) electronic boards degrade in offshore conditions. The model was trained with data on temperature, pressure, vibration, lifetime, and fault history. It achieved numerical convergence after 20 iterations, with a maximum log-likelihood of 38653.8. This indicates that the optimized parameters accurately represent the statistical features of the operational data.

The HMM identified four hidden degradation states: Low, Moderate, High, and Extreme. It estimated their probabilities over time. The findings revealed that 63% of devices operated under Low-Risk conditions, 30% under Moderate Risk, 5% under High Risk, and only 2% under Extreme Risk. This distribution matches real offshore operating conditions, where most tools stay within safe limits and only a few faces critical degradation. Temperature and vibration were the main factors influencing risk changes, while pressure mainly triggered and increased environmental effects.

The model also showed consistent degradation behavior over time, with no unrealistic risk reversals. The increasing risk level with operating hours reflects the wear-out phase typical in electronic components that endure extended thermal and mechanical stress.

In summary, the HMM-based framework effectively captures both random and physical aspects of downhole electronic degradation. It offers a practical basis for risk-based maintenance (RBM) and real-time health monitoring of drilling tools. This supports safer operations, reduces unplanned downtime, and leads to more cost-effective maintenance strategies in offshore drilling settings.

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