ÖPTICYCLE

Literature review

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Contents

Change history

Version	Date	Author	Description
1.0	1-05-2023	Whole team	Initial draft
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1.2	20-06-2023	whole team	Finalized version

1 Abstract

This document offers an enhanced understanding of the order life cycle and potential failures that may occur within it. It begins by providing a clear definition of the order life cycle, outlining the stages involved and their significance. Furthermore, it delves into a comprehensive literature review that explores various attributes and pattern detection techniques associated with the order life cycle.

In addition to attributes, the document also investigates various approaches for failure prediction within the order life cycle. It concludes researches on predictive analytics techniques, machine learning algorithms, and statistical models that can be utilized to detect and forecast potential failures. Overall, this enhanced document provides a thorough analysis of the order life cycle and its potential failures. It combines a clear definition, a comprehensive literature review of attributes and pattern detection techniques, and an exploration of different approaches for failure prediction.

2 Introduction

2.1 Order Life cycle

The term "order life cycle" refers to the various stages that an order or purchase goes through from the time it is placed until it is fulfilled and delivered to the customer. It encompasses the entire process of order management, including order placement, processing, fulfillment, and post-order activities. The order life cycle typically varies depending on the nature of the business and industry but generally involves the following stages:

- ***Order Placement:*** This is the initial stage where a customer submits an order for a product or service. It may be done through various channels, such as in-person, over the phone, or online via e-commerce platforms.

- ***Order Processing:*** Once an order is received, it undergoes processing, which involves verifying the order details, checking inventory availability, and performing any necessary validations or approvals. This stage may also include capturing payment information and conducting fraud checks.

- ***Order Fulfillment:*** After the order is processed, it moves to the fulfillment stage. Here, the products are picked from the inventory, packaged, and prepared for shipment. Depending on the business, fulfillment may involve multiple steps, such as quality control checks, customization, or assembly.

- ***Shipping and Delivery:*** Once the order is packed and ready, it is handed over to the shipping carrier for transportation to the customer's designated location. Tracking information is often provided to the customer to monitor the progress of their order. The delivery timeframe can vary depending on factors such as shipping method, distance, and any potential delays.

- ***Order Confirmation and Customer Communication:*** Throughout the order life cycle, communication with the customer is crucial. After the order is shipped, a confirmation is typically sent to the customer, providing details such as tracking numbers and estimated delivery dates. Any updates or changes to the order, such as delays or out-of-stock items, should also be communicated promptly.

- ***Returns and Exchanges:*** In some cases, customers may need to initiate returns or exchanges for various reasons, such as receiving damaged or incorrect items. The order life cycle may include a separate stage for managing these post-order activities, involving return authorization, product inspections, and issuing refunds or replacements.

In another definition and perspectives, Based on Peng et al (2018) The entire process of the order life cycle, from the order demand communication to finishing the project, can be divided into six stages [12] : creation, preparation, production, delivery, service, and file. Each stage can also be subdivided into smaller stages, as shown in Figure 1.

Here, we can delve into the procedure of OLC in more detail, focusing on a case study within the building material equipment manufacturing industry. The order life-cycle in building material equipment manufacturing enterprises involves the following stages (see Figure 2):

1- Marketing department communicates with the customer and creates the formal order after contract signing.

2- Technical department prepares the necessary technical details and shares the material plan with the procurement department, the Bill of Materials (BOM) with the production department, and outsourcing plans with cooperative manufacturers.

3- The procurement department checks inventory, determines the delivery date, selects suppliers, and creates a purchase order based on the material plan.

4- The outsourcing factory receives the outsourcing order requirements, schedules production, and ensures timely delivery.

5- The production department plans production based on the BOM and delivery date, assembling the product. The quality department conducts timely inspections of materials, outsourced parts, and in-house components, storing them in the warehouse after inspection.

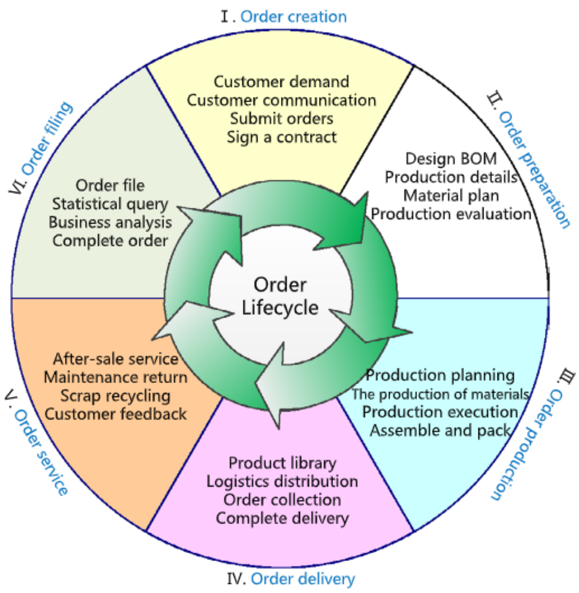

Figure 1: Order Life Cycle

6- The marketing department coordinates with third-party logistics partners for product delivery, informs the customer about product arrival, and provides ongoing after-sales service.

2.2 Possible disturbances in Order Lifecycle

There are some root causes that makes an order imperfection that can be categorized as below:

2.2.1 Order Handling/Item Modifications

2.2.2 Updating orders

- Item Added: Customer changed their mind or realized they needed an additional item after placing the order.
- Item Removed: Customer changed their mind or no longer required a specific item.
- Quantity Changed: Customers realized they needed more or fewer quantities of a particular item.

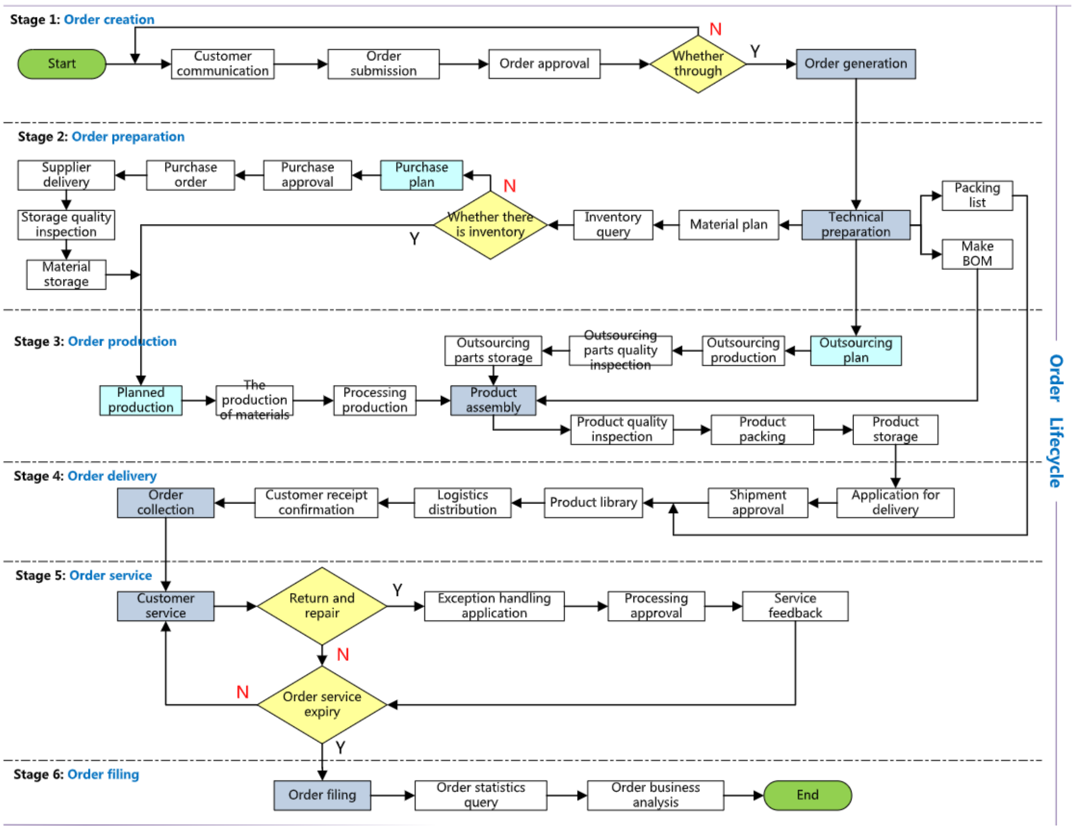

Figure 2: Business process of the order lifecycle

2.2.3 Reacting to issues

2.2.4 Money Modifications

- Card Details: Customer provided incorrect or outdated payment information.
- Discount: This issue can be caused by both customers (if they enter the discount code incorrectly or fail to meet the discount requirements) and IKEA (if there are technical glitches or errors in their discount application system
- Payment Detail: This issue is primarily caused by IKEA, as they handle the payment processing. However, customers may also contribute to payment detail issues if they provide incorrect or incomplete payment information
- Price: This issue is typically caused by IKEA, as they are responsible for setting and maintaining accurate prices. However, customers can also encounter pricing discrepancies if they misunderstand or misinterpret the pricing information provided.
- Service Price: This issue is primarily caused by IKEA, as they are responsible for determining and applying service-related charges. However, customers may also encounter service price issues if they have special requests or if there are miscommunications regarding the pricing of specific services.

2.2.5 Goods Handling

- Cost per touch IKEA inventory management strategies: Cost per touch means that the more times somebody touches the product during the shipment, the more costs the company carries because it needs to pay the procurement and delivery staff. The problems arise when there is a cancellation: Cancelled orders have to have their goods placed back on the shelves. Moreover, Orders being picked from multiple locations and having to be consolidated, unnecessarily.

2.2.6 Service Modifications

- Delivery Time: it caused by customers if they request specific delivery times that are not available or IKEA if there are logistical challenges or scheduling conflicts that result in delays.
- Amount: Inaccurate or incorrect pricing for services. This issue is typically caused by IKEA, as they are responsible for setting the prices and ensuring their accuracy. However, customers can also contribute to pricing discrepancies if they provide incorrect information or misunderstand the pricing structure.

- Service Time: Delays or scheduling conflicts with the estimated service time. This issue can be caused by both customers if they request services at busy times or fail to provide necessary information and IKEA if there are internal scheduling issues or unexpected delays.

- Item Quantity: Errors in determining the correct quantity of items for services. This issue is primarily caused by customers, as they are responsible for accurately specifying the quantity of items they require. However, IKEA may also play a role if there are errors in their systems or if the customer's specifications are not properly communicated or understood.

- Status: Issues with updating or tracking the status of the service. This issue can be caused by both customers (if they fail to provide accurate contact information or if there are communication issues) and IKEA (if their systems or processes for updating and tracking service status are flawed.

- Capacity: Insufficient capacity or resources to fulfill the requested service. This issue is typically caused by IKEA, as they are responsible for managing their resources and ensuring they can meet customer demand. However, customers can also contribute to capacity issues if they make large or unexpected service requests without prior arrangement.

- Provider: Problems related to the availability or assignment of service providers. This issue is primarily caused by IKEA, as they are responsible for managing their workforce and ensuring adequate staffing. However, customers may also encounter provider-related issues if they have specific preferences or requirements that cannot be accommodated by the available service providers

2.2.7 Order Delays

- Item: Delayed availability or backorders for specific items. This issue is primarily caused by IKEA when they experience delays in receiving or restocking specific items. It can also be caused by external factors such as supply chain disruptions or manufacturing delays. Customers may be affected by delayed availability or backorders when the items they desire are not immediately in stock.

- Backordered: Inventory shortages or delays in restocking certain products. This issue is caused by IKEA when they experience inventory shortages or delays in restocking specific products. It can occur due to various reasons such as high demand, production issues, or logistical challenges. Customers may encounter back ordered items when the desired products are temporarily unavailable.

- Blocked: Issues or restrictions preventing the fulfillment or delivery of the order. This issue can be caused by both customers and IKEA. Customers may encounter order blocking if they fail to meet certain requirements, such as providing complete or accurate information, or if they violate terms and conditions. IKEA may also impose restrictions or encounter issues that prevent order fulfillment or delivery, such as legal constraints, regulatory requirements, or unforeseen circumstances.

- High-capacity utilization at the supply source: This occurs when the supply source is operating at or near its maximum capacity. The root causes for high capacity utilization can include increased demand for the product, inadequate capacity planning, supply chain disruptions, or production inefficiencies. It may result in delays, backorders, or difficulties meeting customer demand.

- Inflexibility of supply source: This can arise from factors such as outdated technology, rigid production processes, or limited supplier options. The lack of flexibility can lead to challenges in responding to market fluctuations, customizing products, or meeting customer-specific requirements

- Poor quality or yield at the supply source: When the supply source produces products with poor quality or low yield, it can be due to various factors. These can include issues with raw materials, substandard production processes, inadequate quality control measures, or insufficient employee training. Poor quality or yield can lead to customer dissatisfaction, increased returns or rejections, and additional costs associated with rework or replacement

- Excessive handling due to border crossings or changes in transportation modes

2.2.8 Order return

- Defects: This issue is primarily caused by IKEA if they produce or supply products that have defects. It can include problems such as manufacturing defects, faulty components, or malfunctions. Customers may encounter defects in the products they receive, which can affect their quality or functionalit

- Quality issue: This issue is primarily caused by IKEA if they produce or supply products with subpar quality. It can encompass issues such as poor craftsmanship, low-grade materials, or inadequate durability. Customers may experience a lack of satisfaction or dissatisfaction with the overall quality of the product

- Lack of information: Insufficient or unclear information provided to the customer .IKEA is responsible for providing accurate and sufficient information about their products and services. However, customers may also contribute to the lack of information if they fail to seek clarification or provide complete information regarding their needs or expectations.

- Late delivery: Delays in delivering the order(This issue can be caused both by IKEA if they experience logistical challenges or delays in their delivery process. It can occur due to factors such as high demand, transportation issues, or unforeseen circumstances. Customers may face delays in receiving their orders, resulting in inconvenience or frustration and customer if a customer changes the delivery address after placing an order, it can contribute to a delay in delivery. In such cases, the customer's request to change the delivery address may require additional processing time or necessitate rearranging the logistics of the delivery. This change could lead to a delay as the delivery team may need to adjust their route or schedule to accommodate the new address).

2.2.9 SAC (Service Action Center) Creation

Customer inquiries or complaints that require further support or resolution.

2.2.10 Failed to Pickup

Customer failed to pick up their order from the designated pickup location.

2.2.11 Changes in the source of supply

This occurs when there are alterations in the suppliers or vendors providing the necessary materials or products. Root causes can include supplier bankruptcy, changes in business relationships, shifts in sourcing strategies, or disruptions in the supply chain. Changes in the source of supply can impact the availability, quality, or reliability of the materials or products, leading to delays, disruptions, or the need for the requalification of new suppliers.

2.2.12 Variations in transportation plans or modes of transportation

Root causes for variations in transportation plans or modes can include factors such as changes in shipping routes, fluctuating fuel costs, transportation provider limitations, or disruptions in logistics operations. These variations can result in delays, increased costs, inefficiencies, or challenges in coordinating the movement of goods from the source to the destination.

2.2.13 Exposure to environmental hazards

This refers to the risks posed by environmental factors that can impact the supply chain. Root causes can include natural disasters, extreme weather conditions, pollution incidents, or other environmental events. Exposure to such hazards can lead to disruptions in production, transportation, or storage, causing delays, damages, or even supply chain breakdowns.

2.2.14 Changes in Regulatory requirements

Root causes for changes in regulatory requirements can include updates in local, national, or international regulations, compliance mandates, or industry standards. Changes in regulations can impact the sourcing, manufacturing, transportation, or distribution processes. Failure to comply with new requirements can result in disruptions, penalties, additional costs, or delays in obtaining necessary certifications or approvals.

3 Review of Literature

3.1 Attributes or Pattern Detection Techniques

Sequential-based techniques and non-sequential based techniques are two different approaches to feature extraction.

3.1.1 Sequential-based techniques

Sequential-based methods consider the temporal sequence of events recorded in order lifecycle logs. They concentrate on identifying features or patterns that represent the dynamism and sequential dependencies present in the data. These methods are especially useful when understanding failure scenarios depends on knowing the sequence of events. Sequential-based approaches include the following examples:

- ***Sequence Mining:*** In order to do this, the order lifecycle logs must be mined for regular sequential patterns or subsequences. Its goal is to find repeating patterns of incidents or behaviors that result in failures or suggest the possibility of future failures. Sequence mining can also make use of GSP (Generalized Sequential Pattern) or PrefixSpan algorithms.

- ***Time Series Analysis:*** When there is a temporal component to the order lifecycle logs, time series analysis techniques are used. These techniques examine historical patterns and trends to find possible failure indications. Based on the previous order data, future behavior can be predicted and modelled using strategies like ARIMA, SARIMA, or exponential smoothing.

- ***Recurrent Neural Networks (RNNs):*** A group of neural networks called RNNs are built to process sequential data. The order lifecycle logs offer the capacity to record long-term dependencies and temporal correlations. To extract sequential patterns and predict potential failures, RNN architectures like Long Short-Term Memory (LSTM) or Gated Recurrent Unit (GRU) might be employed.

3.2 Different approaches for Failure Prediction

3.2.1 Non-sequential based techniques

Non-sequential based strategies do not explicitly take the chronological order of occurrences into account. Regardless of how failures occur in sequence, they concentrate on identifying information or patterns that are important for failure prediction. These methods are appropriate when collecting the overall qualities and relationships in the data is the main focus and the sequencing of occurrences may not be as important. Non-sequential based approaches include, for instance:

- ***Statistical Feature Extraction:*** The process of obtaining statistical features, such as mean, median, standard deviation, or percentiles of pertinent attributes, from order lifecycle logs is known as statistical feature extraction. These properties and general distribution of the data are captured by these attributes.

- ***Feature Importance Techniques:*** Each feature in the order lifecycle logs is evaluated using feature significance methodologies for relevance and predictive power. Based on the features' contributions to failure prediction, they rate or score them. Methods like feature importance scores, permutation importance, or information gain can be used for this.

- ***Correlation Analysis:*** Correlation analysis helps identify the relationships between different attributes in the order lifecycle logs. By analyzing the correlation coefficients, one can determine which attributes are highly correlated with failure occurrences.

- ***Domain Knowledge-based Feature Extraction:*** Utilizing specialized knowledge and insights in the pertinent domain is required for domain knowledge-based feature extraction. It involves designing features based on data provided by subject matter experts, business regulations, or recognized risk factors.

The requirements of the project and the type of the order lifecycle records will determine the strengths and usability of both sequential-based and non-sequential based approaches. To extract a comprehensive set of traits that can aid in the prediction of potential failures, it is frequently advantageous to investigate and combine both approaches.

- A study by H. Kamel, discussed the use of artificial intelligence to develop a model that can accurately forecast a machine's state in terms of the likelihood that a failure will occur [11]. The study made use of a synthetic dataset that depicts a realistic scenario in which sensors are linked to a machine to track failure incidences and keep track of its state of health. The classification of the machine's state as malfunctioning or operational was done using artificial neural networks. The output answer, which may be true or false, was taken into account as the machine's failure condition. An artificial neural network was trained, and it was able to accurately forecast the machine's state. The complexities of using artificial intelligence in the realm of predictive maintenance were found to be around achieving a high quality data.

- Noshi et al used both descriptive visual representations like Mosaic and Box Plots and prediction techniques like Artificial Neural Networks (ANN) and Boosted Ensemble trees [10]. On eighty land-based wells, 20 of which had casing and tubing failures. The study evaluated 26 different features gathered from drilling, fracturing, and geology data using a predictive analytics software and python coding. By employing both descriptive and supervised ML algorithms, this work aims to shed light on operational issues and use a data analytical strategy to identify potential causes of casing failures.

3.2.2 Process Mining based methods

- Wang proposed a deep learning based predictive process mining approach to predict possible future activities and completion time in the manufacturing lifecycle of a job-shop [1]. The manufacturing attributes were extracted using techniques like CART, PCA, and KMC. Following this, a Bidirectional LSTM Model with attention mechanism was developed, and trained with the extracted manufacturing attributes to predict the future activities that are to take place and the estimated time of completion for all the activities in total.

- Razo et al. employed the concept of Adjacency Matrix from Graph Theory in predictive process mining (named as Adjancency Matrix Deep Learning Prediction) to predict the immediate next event in any process using **sequence of events (activities) as attributes** [2]. Here, each event log was transformed into a n x n adjacency matrix where n is the number of unique activities involved in the process. This process of creating adjacency matrix is repeated for second and third order consecutive activities/events to extract the maximum eigen value for the same. Finally, the training data attributes include, the first order adjacency matrix, the maximum eigen values of second and third order consecutive events, and is now a three-dimensional data (m x n x n where m is the number of event logs and n is the number of unique activities). After this, a Neural Network Model with 3 layers was trained with the transformed three-dimensional data. The method was validated on eight different datasets and turned out to perform better than all the existing next-event prediction models.

- Mamadou et al. proposed a machine learning approach to detect business process failure using predictive process mining [3]. An example of a loan application is considered as the business process, and repetition of an event more than three times is considered a failure. **Non-sequential categorical and continuous attributes** including number of activities, and the last activity are considered for each loan application with which four ML classification models: Random Forest, Decision Tree, Logistic Regression, and Multi-Layer Perceptron.

- Diaheme et al. proposed a deep learning approach to detect process failure in loan application same as Mamadou et al [3] [4]. Convolutional Neural Network and Recurrent Neural Network models were trained with the **Non-sequential categorical and continuous attributes**. Furthermore, the CNN and RNN models were explained with a well-known Explainable AI method: SHAP.

- Camara et al. introduced a method to bridge data mining and process mining in the context of activity failure [5]. Being a data mining approach to accomplish predictive process mining, the causal attributes (mainly **non-sequential**) associated to failure are derived such as origin event, time duration, number of available resources to meet activity requirements, number of specialists required to finish the activity etc. ML and DL models are to be trained using these attributes for predicting future activity failure.

- Describes a method for predicting the occurrence of cracks in metal sheets during the deep drawing process [6]. The goal is to predict these cracks before they actually happen in order to prevent process failures. The method uses a recurrent neural network architecture called LSTM (Long Short-Term Memory) for both classification and regression tasks. Before training the models, the data is pre-processed and split into training and test sets. The training data is augmented to balance the number of good and bad strokes. The classifier is trained to classify strokes as good or bad, while the regressor is trained to predict the strain gauge signal. The models are evaluated using cross-validation techniques, and their performance is measured in terms of accuracy, true positive rate, false positive rate, and other metrics. In the classification model, the sensory data from strain gauges and flange retraction lasers is processed using a wavelet transform, which converts the raw signal into two feature vectors representing the power of specific time ranges and frequency characteristics of the signal. These feature vectors are then fed into the LSTM network, which predicts the probability of crack occurrences in the future. The regression model is trained to forecast the strain gauge signal. The regressor takes inputs such as the predicted probability of crack occurrence, the filtered signal, locally differentiated signals representing different time scales, and the fast Fourier transform of the signal. It uses this information to predict the strain gauge signal's course and estimate the crack occurrences' timing. As a result, the classifier accurately predicts crack occurrences, and the regressor accurately forecasts strain gauge signals, especially when cracks are likely to occur. In some cases, the regressor may be unable to accurately determine the timing of crack occurrences.

- Introduces DeepLog, a framework for online anomaly detection in system logs using a recurrent neural network called Long Short-Term Memory (LSTM) [8]. Inspired by the structure of natural language, DeepLog treats log entries as sequences and leverages LSTM to learn patterns from normal system execution. DeepLog considers both log keys and metric values in log entries for detecting different types of anomalies. It only requires a small training dataset of normal log entries and achieves high detection accuracy on unseen log entries. DeepLog also builds workflow models from log entries to aid in problem diagnosis. It can adapt to new log patterns by incorporating user feedback and dynamically updating its weights. The paper demonstrates the effectiveness of DeepLog on large log datasets and its ability to incrementally learn and adapt to new system execution patterns.

- The paper proposed using Hidden Markov Models(HMM) to improve the reliability of machinery systems [9]. In the context of machinery systems, failures are often preceded by specific sequences of events, which can be detected using an appropriate HMM. Traditional methods like lifetime models or survival functions are used to estimate the lifespan of a system. However, these methods only consider the elapsed time in estimating the end of a system's life. The goal of this paper is to validate the use of HMMs as an alternative approach. The paper starts by using a synthetic HMM model of degradation to generate event sequences. This synthetic model is inspired by a real process and allows the adjustment of the failure rate by changing model parameters. All the parameters of this synthetic model are known, providing reference values that can be evaluated using different indicators. Classical survival functions used in reliability analysis are then computed on these synthetic sequences, validating the behavior of the synthetic model. The results show that as the failure rate increases, the system's lifetime duration decreases. This confirms that a four-state, left-to-right HMM topology can effectively represent the degradation level of a system.

In the second part of the paper, the HMM approach is applied to a real case where the degradation levels are unknown. The degradation estimates obtained from the HMM approach are compared with the results from classical survival functions used in the first case. The paper demonstrates that the HMM approach, which considers the events collected about a system rather than just the elapsed time, is more efficient in estimating the degradation level. In other words, the HMM approach provides better insights into the current state of degradation of a system compared to traditional survival functions.

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