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Composite Hybrid Framework for Through-Life Multi-Objective Failure Analysis and Optimisation

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ABSTRACT Complex engineering systems include several subsystems that interact in a stochastic and multifaceted manner with multiple failure modes (FMs). The dynamic nature of FMs introduces uncertainties that negatively impact the reliability, risk, and maintenance of complex systems. Traditional approaches of adopting standalone techniques for managing FMs independently at various stages of the asset life cycle pose challenges related to utilisation, costs, availability, and in some cases, accidents. Therefore, this paper proposes a composite hybrid framework comprising four independent hybrid models for comprehensive through-life failure management and optimisation. The first hybrid model entails failure mode, effects, and criticality analysis (FMECA) and fault tree analysis (FTA) to identify critical FMs and overall subsystem failure rates. The second hybrid model analyses FMs caused by multiple subsystems using hybrid dynamic Bayesian discretisation. The third hybrid model adopts a hybrid Gaussian process regression machine learning technique to evaluate wear loss. The fourth hybrid model evaluates the overall risk using a Bayesian factorisation and elimination method based on multiple failure causes. Finally, a decision-making step is used to evaluate the results of the previous four steps to decide an appropriate maintenance strategy. The proposed method is verified through a case study of a UK-based train operator's pantograph system. The results show that the maintenance inspection intervals and strategy obtained using the proposed framework strike a good balance between safety and fleet availability.

INDEX TERMS Multiple failure modes, reliability, risk, maintenance, hybrid framework.

I. INTRODUCTION

The transportation industry is experiencing a surge in the demand for faster movement of goods and people. At the same time, the engineering systems within such transport systems are becoming increasingly complex. Therefore, critical subsystems must have improved reliability to ensure that they continue to perform as designed. Various techniques can be implemented to reliably verify the performance of an asset across different life cycle phases. For example, in the railway industry, rapid expansion, innovations, upgrades and rising passenger numbers have led to increased technical failures and accident risks [1]. A 22-year analysis of causal factors of rail derailment in the US revealed that technical failures caused 18.2% of derailments with multiple casualties and 4.3% of train collisions [2]. Furthermore, an analysis of the causes of train derailments from the US Federal rail transportation database indicated that equipment-related failures contributed to 40.8% of derailment accidents [3]. A systematic analysis of the Edge Hill railway accident of May 1999 and the Paddington railway accident of October 1999 in the UK revealed that failure of the train's automatic warning system in addition to lack of effective maintenance strategies played critical roles in both accidents. These findings suggest that in complex engineering systems, a degree of correlation often exists between equipment failure management and accidents [4], [5].

Given the criticality of complex engineering systems such as rolling stock and the causal factors that can lead to catastrophic accidents, several studies [6]–[9] have investigated various decision-making techniques related to reliability, risk, and maintenance to support engineering asset management and failure analysis. These techniques can be useful in asset management decision-making. However, they suffer from several limitations especially chronic failures, unavailability, and excessive cost [10]– [12]. Fortunately, these limitations can be overcome by using hybrid models that enable the strength(s) of one or more techniques to compensate for

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TABLE 1. Summary of failure classification and their corresponding analysis techniques.

Techniques	Random failure (single cause event)	Random failure (multiple cause events)	Systematic failure (with temporal random cause event)	Systematic failure (with external & environment cause event)
FMECA and FTA	Practical, accurate, and straightforward for one event failure [23], [24]	Not suitable for multiple events [10], [23], [25]	Inadequate with complexity and inaccuracies [10], [25], [23]	Inadequate with complexity and inaccuracies [10], [23], [25],
Bayesian network (BN) and Dynamic Bayesian discretisation (DBD)	Less accurate and overly complicated for one event [26], [27]	Effective and accurate for multiple events failure analysis [26] - 28]	Less accurate because of model computational complexities [26], [27]	Less accurate due to model computational complexities [26], [27]
Machine learning (ML) regression with non-linear covariance function	Less accurate and overly complicated for one event [29] - [31]	Less accurate, insufficient causality and overly complicated with two random events [29], [30]	Better accuracy for modelling systematic failures with underlying randomness [32] - [35]	Less accurate, insufficient causality due to combinations of failures [29], [30]
Bayesian factorisation and elimination with n-fold convolution	Less accurate and overly complicated for one event [36] - [39]	Less accurate and overly complicated with two random events [36] - [39]	Less accurate, more resources with modelling complications and challenges [36] - [39]	Effective and more accurate for combining multiple failures from external and environmental conditions. [40]

the limitation(s) of others [13]–[17]. Two significant failures can affect railway rolling stock subsystems: systematic and random failures [18]. Random failures are hardware failures represented by statistical distributions, whereas systematic failures are attributed to errors in system life activities that cause the product to fail deterministically under a series of inputs or conditions. Thus, random failures can be tracked statistically, and their probability can be estimated. Random failures associated with a single subsystem occurrence are called single-event random failures, while those associated with multiple subsystem occurrences are called multiple events random failures. These random failures cannot be eliminated, and therefore, there is a need to focus on detecting and managing random failures [18]–[22]. Systematic failures are caused by incidents for which statistical data are rarely available, which makes it impossible to estimate their likelihood. Systematic failures can be repeated if a set of events that trigger these failures can be replicated exactly. Consequently, systematic failures can be further categorised into systematic failures with underlying temporal random (hardware event) behaviour and those triggered by environmental and external factors (e.g., human error, electromagnetic interference, temperature, and weather conditions). Furthermore, systematic errors can be minimised by implementing a continuous and robust process improvement programme [18]–[22]. Major railway rolling stock failures can be classified into random failures with a single cause event, random failures with multiple cause events, systemic failures with a temporal random cause event, and systematic failures with external and environmental causes. Table 1 lists the four most common classes of railway rolling stock failures and their corresponding failure analysis methods.

FMECA and FTA are the most common railway rolling stock subsystem techniques used for random failures with a single cause event [23], [24]. FMECA is suitable for bottom-up analysis, while FTA is commonly used for top-down events, revealing the logical relationship between a single event and its component events. Both methods are compact and yield computational complexities with risk factors of different weights and time dependencies, which can lead to challenges and inaccurate results for random events caused by multiple subsystems and systematic failures [10], [23], [25]. The Bayesian network (BN) and Dynamic Bayesian discretisation (DBD) allow for all discrete and ordinal continuous data analysis for all qualitative and quantitative failure analysis. Furthermore, BN and DBD are suitable for handling multiple sequential and time-dependent subsystems with efficient computational time and accuracy. The BN and DBD can adequately handle prior information to allow for evidence-based propagation [26]–[28]. While BN and DBD address random failures with multiple random events, they also have some drawbacks. For example, BN and DBD require that many states be developed for each scenario, which increases computational challenges and impacts accuracy [26], [27]. Furthermore, for systematic failures, each specific scenario must be replicated, and the BN must be developed separately, which can be time consuming and challenging [41]. Moreover, stochastic Petri nets, Monte Carlo simulation, and Markov chains can be used for random failures with multiple caused events analysis with a varying degree of accuracy, data handling capabilities, and computation time [42], [43].

ML techniques and algorithms incorporate embedded techniques for diagnosing non-linear and irregular systematic failures with random cause failure events such as irregular wear loss, fatigue, cracks, and others [32]–[35]. ML techniques (e.g., supervised regression with kernel functions and unsupervised artificial neural networks) can adapt rapidly, compared to BN and DBD when predicting the integrity loss of critical railway rolling stock subsystems subjected to systematic failures with temporal random events [35], [44]–[48]. However, ML sometimes suffers from lack of accuracy, inconsistency, and discrepancies when multiple sources and different weights are considered simultaneously [29]–[31]. Systematic failures with external and environmental causes often lead to human error, technical defects, and biases, which in turn increase the probability of accidents such as derailments, collisions, and fires [40]. While these failures can sometimes be addressed individually via ML techniques, their combined effects can be better analysed using risk aggregation techniques such as Bayesian factorisation and elimination (BFE) with n-fold convolution method, as this offers better levels of accuracy [36], [37]. BFE with n-fold convolution can evaluate the combined effects of the multiple frequencies of failures and consequences to enable overall risk prediction associated with systematic failures with external and environmental influences [38], [39]. Therefore, there is a need to address these four major classes of failures comprehensively. A holistic approach that integrates the various techniques can serve as the basis for comprehensive asset management decision-making.

A. REVISITING HYBRID SYSTEMS FOR FAILURE MANAGEMENT

Hybrid systems are classified into two main groups: hybrid models that produce their own outputs and hybrid modelling that integrates the outputs obtained from several different models [49]. The present study focuses on the use of hybrid modelling to support asset management decision-making in engineering systems. Studies [16], [49]–[51] highlighted that hybrid models are also used for asset management failure analysis and operational decision-making for complex engineering systems. Assuming that the synthesis of industrial system failures and the selection of cost-effective maintenance techniques account for a considerable part of the total downtime [42], [51], [52], our objective is to propose a hybrid framework that seamlessly integrates and optimises different established hybrid models to exploit their strengths. Yunusa-Kaltungo *et al.* [53], Morgan *et al.* [54], recently postulated that when many hybrid models are integrated, owing to their intrinsic dynamism, uncertainty, and multi-dimensionality, they can provide sufficiently representative solutions to real-life industrial problems. Morgan *et al.* [55] considered a realistic case study and investigated the benefits of integrating two or three hybrid methods. Howick *et al.* [56] established a hybrid system focussed on the construction sector's poor global safety record to reveal design vulnerabilities and predict possible injuries.

To improve the reliability, availability, and safety of engineering systems, studies have investigated dynamic machine learning (ML) techniques for early fault detection and diagnosis in asset-intensive industries such as the railway, oil and gas, power generation, and process industries [42], [57], [58]. Dynamic probabilistic models such as Bayesian networks (BNs), stochastic Petri nets, and Markov analysis have also been implemented in hybrid forms that consist of at most two techniques for the dynamic failure analysis of complex systems. However, the availability of composite hybrid approaches that consist of more than two models, particularly in reliability engineering and asset management, remain limited [42], [59], [60]. In a complex engineering system such as the railway rolling stock, the complexities of some failure modes (FMs) such as wear loss, fatigue, cracks, human error, and severe environmental conditions can occur independently or simultaneously in a non-linear manner, making failure diagnosis challenging for most existing two- or three-technique hybrid models. This is perhaps why some recent research developments in hybrid ML and statistics have focussed on enabling offline and online failure diagnosis for wear loss in complex components. The application of ML techniques such as Gaussian mixture regression (GMR) support vector machines (SVMs), whereas multiple linear regression (MLR), Gaussian process regression (GPR), and artificial neural networks (ANNs) [31], [34], 46], offer reasonable classification and separation of individual operating conditions during faults diagnosis; however, they have also been criticised for providing limited information about the physics of FMs, which may hinder their ability to achieve comprehensive asset management decisions [58], [61]. Specifically, both GMR and GPR require a large number of datasets and incur high computational costs for accurate and routine failure diagnosis; MLR lacks the consistency to always connect causal inputs to failure outputs [62]; ANN suffers from inconsistent neural network weight allocation values, which in turn produces inconsistent outputs [63]; and SVM uses data subsets (i.e., smaller datasets) that may lead to inaccuracies [64].

Given the complexities of failure analysis and asset management decision-making for different life cycle stages, this study proposes a novel composite hybrid framework that integrates four independent hybrid models with a decision-making step for application in various life cycle stages. The proposed framework contributes to existing literature in two distinct ways: (1) it allows for comprehensive reliability analysis irrespective of the life cycle stage and FMs, and (2) it ensures holistic and well-informed decision-making for the maintenance strategy in consideration of the asset performance in any life cycle stage. The remainder of this paper is organised as follows: Section 2 presents the proposed composite hybrid framework. Section 3 discusses the case study used to test its applicability in real-life scenarios, including the analysis of core findings. Finally, Section 4 concludes the study and offers highlights of future research directions.

II. PROPOSED COMPOSITE HYBRID FRAMEWORK

The proposed composite hybrid framework comprises four independent hybrid models and an asset maintenance decision-making step that originates from the outputs of the four individual hybrid models, as shown in Fig. 1. The first hybrid model entails the failure mode, effects, and criticality analysis (FMECA) and fault tree analysis (FTA) techniques. FMECA highlights all potential FMs associated with the subsystem under study and the corresponding criticality based

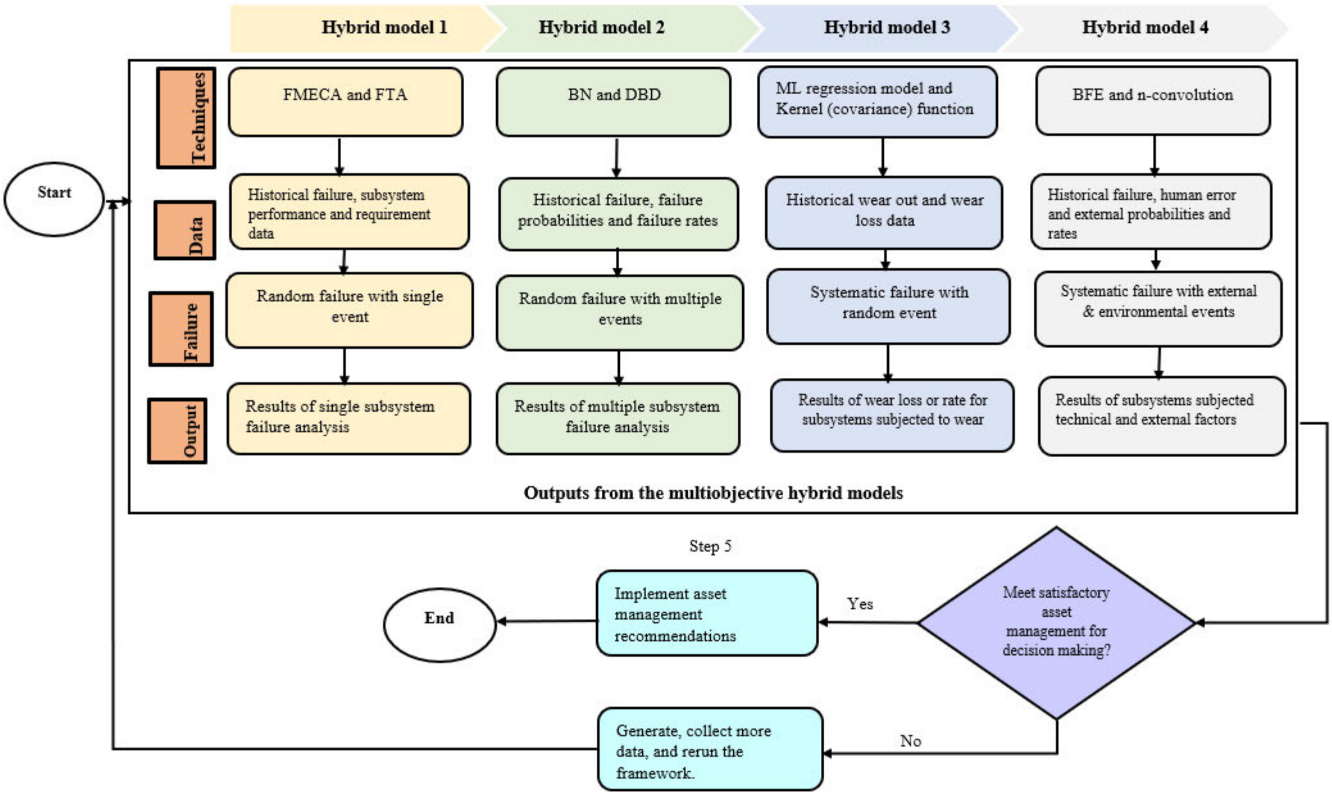

FIGURE 1. Composite hybrid framework for optimising and improving asset management.

on the risk priority number (RPN). FTA estimates the subsystem's overall steady-state failure rate and illustrates the logical relationship between the top subsystem failure events and the corresponding component FMs. After the FMs are identified, the second hybrid model uses the hybrid inference obtained with the dynamic Bayesian discretisation (DBD) technique to analyse FMs related to multiple components, interfaces, and external effects in the subsystem under study. The DBD technique enables qualitative and quantitative (both discrete and continuous data) evaluations of the FMs in the subsystem under study to ascertain their overall effects. The third hybrid model applies the GPR ML technique to subsystem components subjected to FMs such as wear loss, fatigue, and cracks to predict the wear loss of critical components subjected to non-linear factors such as irregular weather patterns and foreign object debris including dust and leaves. In this study, the FMs were investigated because of their large contributions to railway systems components failures and service disruptions [65]. The fourth hybrid model uses BFE with n-fold convolutions to predict the risk in terms of the overall potential loss arising from multiple sources (internal and external), including the expected changes in frequency and severity of failures owing to changes in asset life cycle. Finally, the decision-making step determines an appropriate overall maintenance strategy as well as the interval for the subsystem and its components, based on the outputs of previous steps. To foster practicality, the decision-making stage of the composite hybrid framework allocates its recommended maintenance decisions based on considerations of safety and organisational resource constraints.

A. THEORETICAL BACKGROUND OF THE PROPOSED COMPOSITE HYBRID FRAMEWORK

The implementation of the proposed composite hybrid framework is systematically achieved through the following steps:

1) STEP 1: HYBRID MODEL FOR FMECA AND FTA

The first step involves determining and evaluating the functions, functional failures, and FMs of the critical components in the subsystem under study. The RPN is used to define and rank critical FMs based on three parameters: severity (S), probability (P), and detection (D). For a subsystem with FMs represented by FM_{hv}, the RPN is calculated using S, P, and D as in [9], [66]:

$$RPN_{hv} = S_{hv} \times P_{hv} \times D_{hv}, \quad h = 1, \ldots, m; \quad v = 1, \ldots, n \tag{1}$$

where h represents FMs and v represents subsystems. Each RPN parameter (S, P, and D) is ranked from 1 (lowest) to 10 (highest). The RPN does not play an important role when choosing an action against FMs; however, it may help in obtaining the threshold values for deciding the areas to focus on [9], [66], [67]. Then, the FTA is applied to estimate the overall failure rate using common FTA symbols such as basic events, AND-gate, OR-gate, and top or intermediate events [23], [68]. Assuming that all basic events are statistically independent and identically distributed (IID) random variables, the probability of the top failure rate events (P_{TE}) for a subsystem connected by both OR-gates and AND-gates is calculated as depicted in (2) - (3) [69]:

$$P_{TE} = 1 - \prod_{i=1}^{n} (1 - P_i) \tag{2}$$

$$P_{TE} = \prod_{i=1}^{n} P_i, \quad i = 1, \ldots, n \tag{3}$$

2) STEP 2: HYBRID DBD MODEL FOR MULTIPLE SUBSYSTEMS AND RELATED FMS

A BN is agnostic to the location of dependent variables with prior probability from the cause and effect of the original FMs. Thus, regardless of the origin and structure of the FMs and related subsystems, BN can predict the joint distribution of a random vector as the product of the conditional probability density (CPD) as follows [70]:

$$P(X_1, \ldots, X_n) = \prod P(X_i | pa(X_i)), \tag{4}$$

where $P(X_i|pa(X_i))$ is the CPD of variable X_1 to X_n given its parent $pa(X_i)$. When the learnt structure of the BN between the multiple FMs is known, the discretised CPD function for each FM can be estimated via the hybrid inference BN and the junction tree technique using the Kullback–Leibler (KL) measure to establish the convergence rule for the DBD function as in [42], [71]–[73]:

$$D(f \parallel g) = \int_s f(x) \log \frac{f(x)}{g(x)} \tag{5}$$

where KL is a distance measure between two density functions f and g, and D is the approximate error of the true and approximate functions $f(x)$ and $g(x)$. The final CPD failure rate between two or more subsystems and interfaces can be predicted regardless of the form, data types, and causal relationships among these subsystems via the convergence iteration technique and stable-entropy-error and low-entropy-error convergence stop rules [42], [71]–[73]:

$$SEE = \left\{ 1 - \alpha \le \frac{S_X^{(\text{l-k})}}{S_X^{(l-k+1)}} \le 1 + \alpha \forall \ k = 1, 2, 3; \quad l = 1, \ldots, n \right\} \tag{6}$$

$$LEE = \left\{ S_i^X < \beta \right\} \tag{7}$$

where n is the maximum number of iterations and $S_X^{(l)} = \sum_{W_j} E_j$ is the approximate relative entropy error.

3) STEP 3: GPR HYBRID MODEL FOR A CRITICAL COMPONENT SUBJECTED TO NON-LINEAR FAILURE SUCH AS WEAR LOSS

GPR is used to analyse the FMs of components subjected to random and non-linear failure such as wear loss variations, due to its ability to offer improved accuracy and predictions through the use of all data points. This is in contrast with other well-established ML approaches such as SVM that only use subsets of data points or MLR that lacks consistency or GMR that generates new sets of data points that can impact accuracy [62], [63]. The input wear values c for a non-linear component with noise variance can be expressed in a linear form as [74]–[77]:

$$y = d^T c + N(0, \sigma^2) \tag{8}$$

where $N(0, \sigma^2)$ is the additive Gaussian noise whose values are independent across the observations c. By combining all y values into a vector, (9) can be expressed as the distribution of y conditioned on the function $d^T c$ as in [74]–[77]:

$$p(y \mid c, C, \mathbf{y}) = N\left(\frac{1}{\sigma^2} c^T A^{-1} C\mathbf{y}, \ c^T A^{-1} c\right) \tag{9}$$

where $A = \frac{1}{\sigma^2} CC^T + \Sigma_d^{-1}$. Because this is Gaussian noise, a non-linear transformation function $\phi(c)$ can be introduced into (9) as follows:

$$p(y \mid c, C, y) = N\left(\frac{1}{\boldsymbol{\sigma^2}} \boldsymbol{\phi}(c)^T A^{-1} \Phi(C)\mathbf{y}, \ \boldsymbol{\phi}(c)^T A^{-1} \boldsymbol{\phi}(c)\right) \tag{10}$$

where $A = \boldsymbol{\sigma}^{-\mathbf{2}} \Phi(C)\Phi(C)^T + \Sigma_d^{-1}$. Given that (10) is also Gaussian, the GPR predictive model for the prior function $d^T c$ can be expressed as follows:

$$y = E\{y \mid c, C, \mathbf{y}\} = \sum_{i=1}^{L} \alpha_i k(c, c^i) \tag{11}$$

where $\alpha = [K(C, C) + \sigma^2 I]^{-1} \mathbf{y}$ can be defined by the kernel function $k(c, c') = \phi(c)^T \Sigma_d \phi(c')$ and variance $var(x) = (k(c, c^i) - \boldsymbol{k}^T(\boldsymbol{c}))(K(C, C) + \sigma^2 I)^{-\mathbf{1}} \boldsymbol{k}(c)$. The square exponential (SE) function is selected as the covariance function to estimate the hyperparameters of the Gaussian kernel as [74]–[77]:

$$k(c, c') = e^{-\frac{\|c - c'\|}{l}} \tag{12}$$

where l is the kernel width.

The prediction performance obtained with (11) can be evaluated using the root mean square error (RMSE) and mean absolute error (MAE) as follows:

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N} (\acute{c}_i - c_i)^2}{N}} \tag{13}$$

$$MAE = \frac{\sum_{i=1}^{N} (|\acute{c}_i - c_i|)}{N} \tag{14}$$

where $\acute{c}_i$ is a set of n expected target values and c_i is a set of n prediction test data.

4) STEP 4: HYBRID MODEL FOR QUANTITATIVELY EVALUATING OVERALL RISK

The overall risk to the subsystem from multiple sources is quantitatively evaluated using the BFE ML method with the n-fold convolution theory. The overall risk model R can be obtained using the general risk estimation formula for n fixed structures as [39], [78]–[80]:

$$R = D_0 + D_1 + D_2 + \ldots + D_n \tag{15}$$

where D_i is the sum of failure consequences or severities for $i = 0, \ldots, n$ that represents IID severity distribution. Assuming that D_i is a derivative of the continuous distribution function g_x, it can be considered a distribution form g_x such that $(D \sim g_x)$, thereby allowing (15) to be evaluated as an n-fold convolution function g_a as follows [39], [78]–[80]:

$$g_a = \sum_{j=0}^{\infty} g^{*k}(x) P(M = n) \tag{16}$$

where $g^{*k}(x) = \int_0^{\infty} g^{*(k-1)}(\text{x-z}) f(dz)$ is a recursive n-fold convolution on the consequence D. Thus, assuming that the frequency of occurrence of a hazard from multiple sources is f and the associated severity or consequence D are mutually exclusive variables, the overall risk aggregation distribution function R can be expressed as follows [39], [78]–[80]:

$$P(R) = f_0 P(R_0) + f_1 P(R_1) + \ldots + f_L P(R_L) \tag{17}$$

where $R_0 = D_0, R_1 = D_0 + D_1, \ldots, R_L = D_0 + D_1 + \ldots + D_L$, and each R_j is a constant n-fold convolution.

5) STEP 5: IMPLICATION OF RESULTS AND MAINTENANCE DECISION-MAKING

By using the outputs from all four hybrid models, as well as considering their implications, an appropriate maintenance strategy and the associated frequency can be selected to manage individual components and the overall subsystem at any stage in the asset life cycle. Planned preventive, corrective, predictive, or risk-based inspection approaches can be used for failure and maintenance management [6], [81], [82].

III. CASE STUDY, DATA COLLECTION, AND ANALYSIS OF FINDINGS

This section discusses the application of the proposed composite hybrid framework. To maintain confidentiality of the train operator considered in the case study and to simplify the discussion, we only present those results that are essential for demonstrating the proposed framework; for example, the scope of FMECA was limited to only critical items and one associated FM. The case study was conducted in collaboration with a UK-based train operator using a four-car EMU vehicle (specifically, four-car EMU $\times$ 48 fleets $=$ 192 cars) to support strategic planning and decision-making for asset management in view of a proposed increase in operating time from 14 to 18 h per day. The proposed framework was applied to the pantograph subsystem only. The pantograph head assembly comprises carbon strips (current conductors) and a carbon carrier (bracket) that conducts electricity from the overhead line. Frames comprising lower, upper, and control rods enable the pantograph head to move vertically and support the weight of the pantograph assembly. Air equipment supplies the required air pressure to enable the lifting device to pneumatically lift the pantograph. The air feed insulates the car from an accidental live electric supply owing to arcing, flashover, or fire. The control assembly allows the pantograph to be controlled by the driver as well as the maintenance team, as shown in Figs. 2(a)-(c). Magnified views of the pantograph head, crack defects of the carbon strip, the space between the carbon carrier, and the carbon strips are shown in Figs. 3(a)-(c), respectively.

TABLE 2. Sample data for train travel distance, carbon strip training and test wear data, and coupling rod MTTF.

Sample data	Train travel distance (km)	Carbon strip training wear data (mm)	Carbon strip test wear data (mm)	Coupling rod MTTF data (h)
1	14,094	9.01	7.90	463,517,645
2	13,669	9.79	8.56	831,098,263
3	9,514	9.74	8.70	916,283,865
4	13,395	9.71	5.99	3,854,435,801
5	13,654	9.86	4.89	2,087,017,661
6	10,223	9.67	5.12	3,285,909,754
7	12,874	7.65	5.70	2,427,469,177
8	16,080	6.62	5.99	792,075,959
9	16,194	6.65	9.17	2,434,296,598
10	16,507	6.36	9.24	123,941,110
11	12,234	6.27	5.12	912,265,628
12	7,354	6.25	4.30	3,125,769,443
13	7,800	6.22	5.70	
14	7,271	5.64	7.80	
15	6,944	9.01	7.90	
16	7,120	9.02		
17	7,870	9.05		
18	8,897	9.45		
19	8,347	9.68		
20	8,384	9.77		
21	8,167	9.82		
22	7,308	9.85		
23	6,996	9.93		
24	9,878	5.18		
25	13,045	5.34		
26	11,914	5.47		
27	14,035	5.89		
28	16,161	6.47		
29	15,405	7.89		
30	14,036	8.56		
31	10,597	8.61		
32	14,094	8.77		

TRAINING AND TEST WEAR DATA, AND COUPLING ROD MTTF

A. CONTEXT

The train operator proposed a mission profile in which trains will run for 18 h per day (compared to the current 14 h per day). Accordingly, the operator aims to propose that the mean time between maintenance (MTBM) of the pantograph should be a minimum of 504 h. The proposed composite

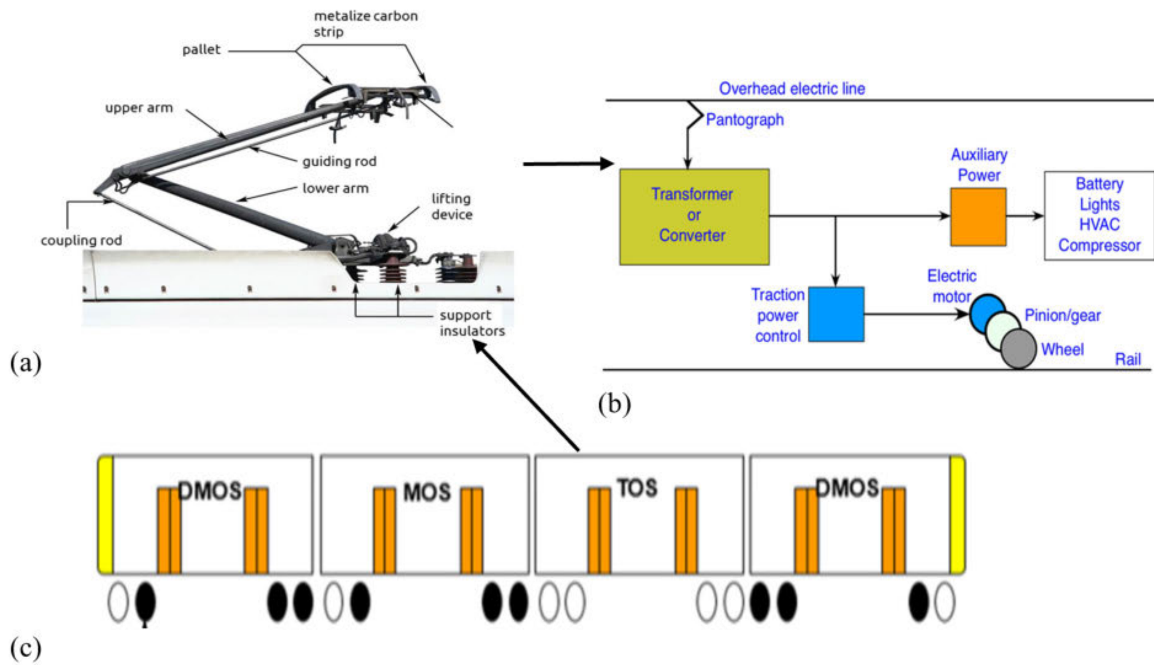

FIGURE 2. (a) Layout of pantograph subsystem [83]; (b) Schematic layout of pantograph and other interface subsystems [84]; and (c) Four-car EMU with pantograph fitted to trailer open saloon.

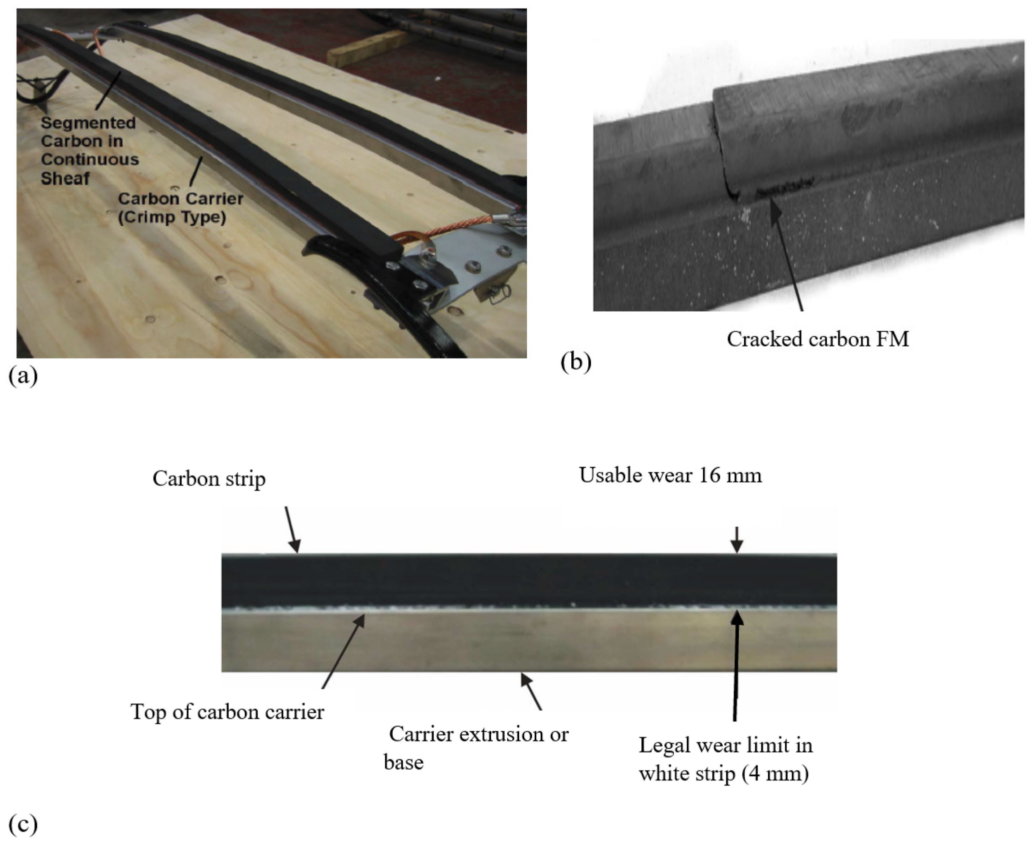

FIGURE 3. (a) Pantograph carbon strip assembly; (b) Example of cracked carbon strip; and (c) Pantograph carbon strip showing usable and wear limits.

hybrid framework was applied to analyse and verify the feasibility and safety of these changes. Table 2 shows some sample data, including:

- operation records from 32 trains over 27 months,
- measurements of 32 carbon strip wear data from five trains using 'go/no go' gauges,
- measurements of 15 carbon strip test wear data from two other train periods.

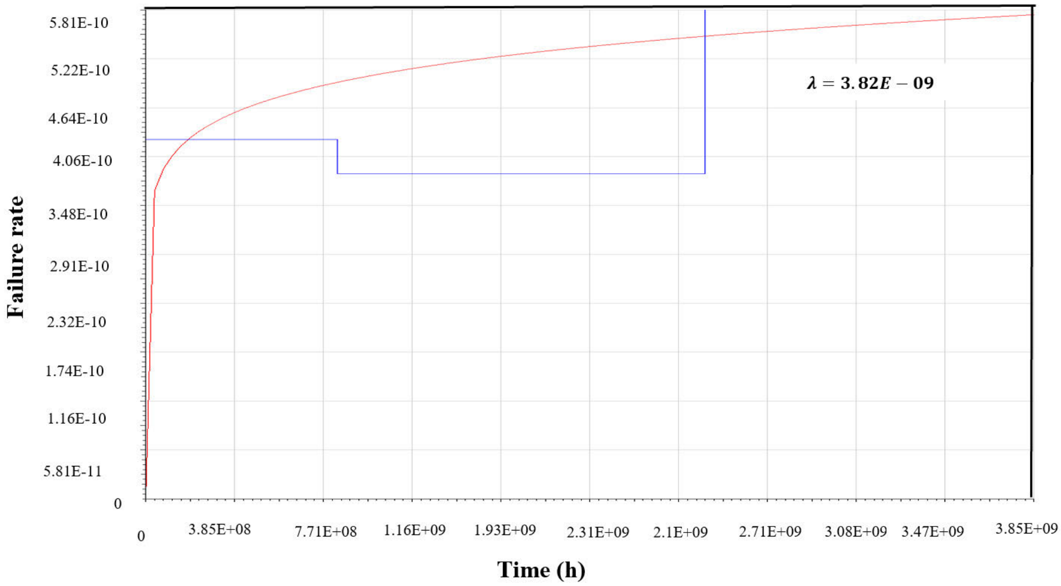

FIGURE 4. Coupling rod failure rate prediction.

TABLE 3. Pantograph subsystem FMECA.

Component	Function	FM	Effects	Part quantity	Part failure rate	S	P	D	RPN	Basic event symbols	Current controls
Carbon strip	Conduct electricity	Wear loss	Degraded power supply	2	1.1E-08	9	2	5	90	A1, A2	3,000 km PM inspection and replace on failure
Carbon carrier assembly (pallet)	Provides contact with overhead line	Carrier assembly fracture	Possible damage to overhead	2	2.5E-10	8	1	5	40	B1, B2	4,000 km PM inspection and replace on failure
Coupling rod	Connects head assembly to control rod	Coupling fracture due to fatigue	Degraded pantograph presentation to overhead line	1	3.82E-09	6	2	3	36	C	5,000 km PM inspection and replace on failure
Upper arm frame	Provides articulation between lower arm and head assembly	Fracture due to impact	Degraded power collection	1	1.3E-09	7	2	3	42	D	5,000 km PM inspection and replace on failure
Lower arm frame	Provides articulation between upper arm and base	Fracture due to impact	Degraded power collection	1	3.4E-09	7	2	3	42	E	5,000 km PM inspection and replace on failure
Lifting device	Pneumatically articulate lower arm	Seal failure	Degraded power collection	1	2.6E-08	7	2	3	42	F	4,000 km PM inspection and replace on failure
Air equipment	Transmits air to operate the pantograph	Poor maintenance adjustment	Degraded contact with overhead wire	1	8.5E-09	6	2	3	36	G	4,000 km PM inspection and replace on failure
Air feed insulators	Electrically insulates vehicle from pantograph assembly	Degradation by moisture ingress	Local electrical arcing	4	5.1E-09	8	2	4	64	H1, H2, H3, H4	4,000 km PM inspection and replace on failure
Control panel assembly	Control pantographs	Unclean air supply	Unable to raise pantograph	1	3.1E-10	8	1	1	8	I	4,000 km PM inspection and replace on failure

The total carbon strip height is 20 mm, of which 16 mm is usable wear and the remaining 4 mm is the legal disposable wear limit. The failure rates for the overhead line (OHL) and main reservoir (MR) were estimated as 2.28×10^{-4} per hour (equivalent to two incidents per year) and 5.7×10^{-5} per hour, respectively. The maintenance error probability for experienced and inexperienced pantograph technicians was considered 74.5% and 25.5%, respectively. MATLAB version

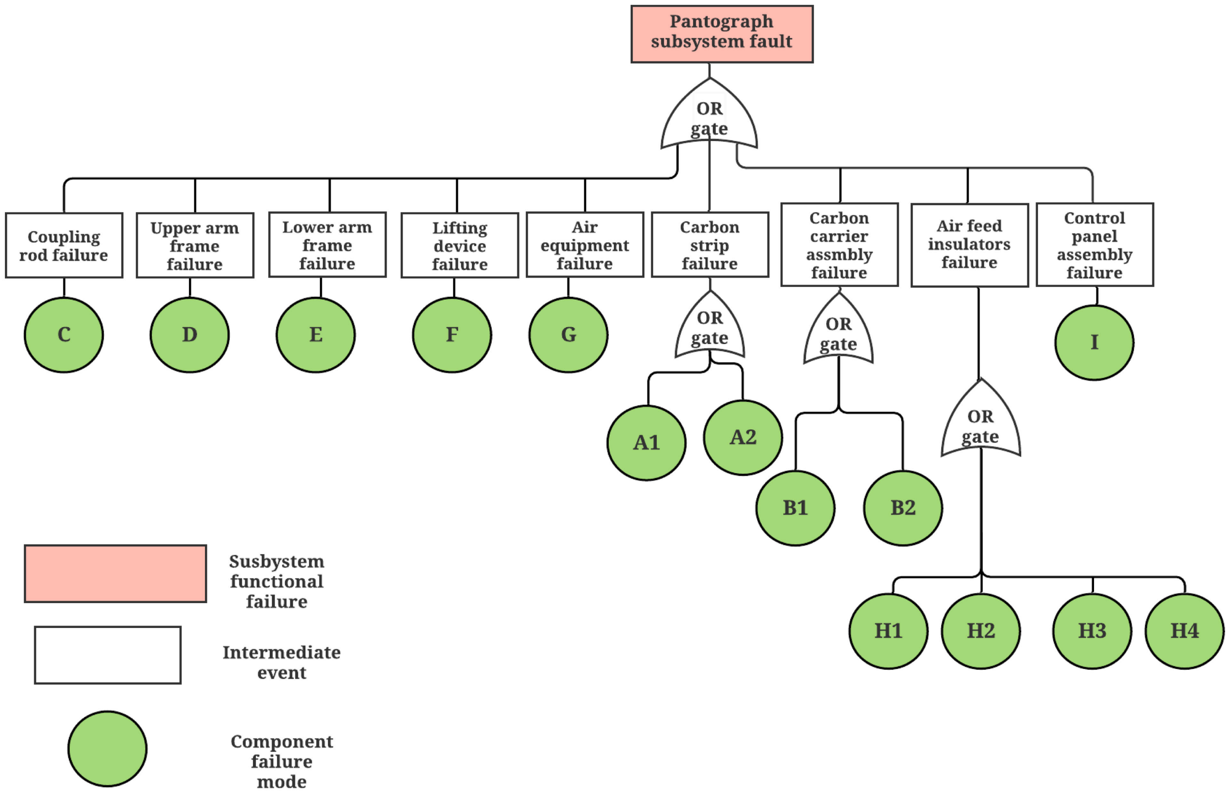

FIGURE 5. FTA of pantograph subsystem.

R2020a, AgenaRisk [85], and Isograph reliability workbench version 15 software were used for the analyses.

B. ANALYSES, DISCUSSIONS, AND IMPLICATION OF RESULTS

This section discusses the results of the proposed composite hybrid framework. Specifically, it highlights the FMECA and FTA analyses (Section 3.2.1), impact of multiple interface subsystem failures (OHL and main air reservoir) and their impacts on the pantograph subsystem (Section 3.2.2), carbon strip wear analysis (Section 3.2.3), quantitative risk evaluation (Section 3.2.4), and implication of the results for maintenance decision-making (Section 3.2.5).

1) FMECA AND FTA ANALYSES

First, FMECA was applied to critical components of the pantograph to establish the function, FMs, effects on the train, number of parts, part failure rate, RPNs and to highlight the current controls. Part failure rates were estimated using the recorded mean time-to-failure (MTTF). For example, Fig. 4 shows the coupling rod failure rate predictions ($\lambda = 3.82 \times 10^{-9}$ per hour) obtained using the MTTF data in Table 2. The same approach was used to obtain part failure rate predictions from the data in Table 3. By using (1)-(3) for the nine critical FMs considered in this study, the carbon strip showed the highest RPN of 90, followed by air feed insulators with an RPN of 64, while the control panel showed the lowest RPN score of 8. FMECA based on Table 3 is limited to only key components of the pantograph that are most relevant to the analysis performed here. FMECA also listed the currently established maintenance controls to handle the potential FMs

TABLE 4. Prior NPT data for DBD computations.

NPT	Failure rate λ per hour	Prior node probability	Node type
Pantograph (PAN)	7.91×10^{-8}	Exp$(-\lambda t)$	Continuous interval (Simulated node)
Main reservoir (MR)	2.28×10^{-4}	Exp$(-\lambda t)$	Continuous interval (Simulated node)
Overhead line Failure (OHL)	5.7×10^{-5}	Exp$(-\lambda t)$	Continuous interval (Simulated node)
Time-to-failure	Synthetic node	If (τ_TRP < 504 h, Failure, Success)	Discrete (Boolean)
Predicted probability of failure or success in MTBM of 504 h when either OHL or DE occurs	Synthetic node	Min $(\tau_{TPAN}, \tau_{TMR}, \tau_{OHL})$	Continuous interval (Simulated node)
Maintenance error	Inexperience, Experience	Discrete node	(0.745, 0.255)

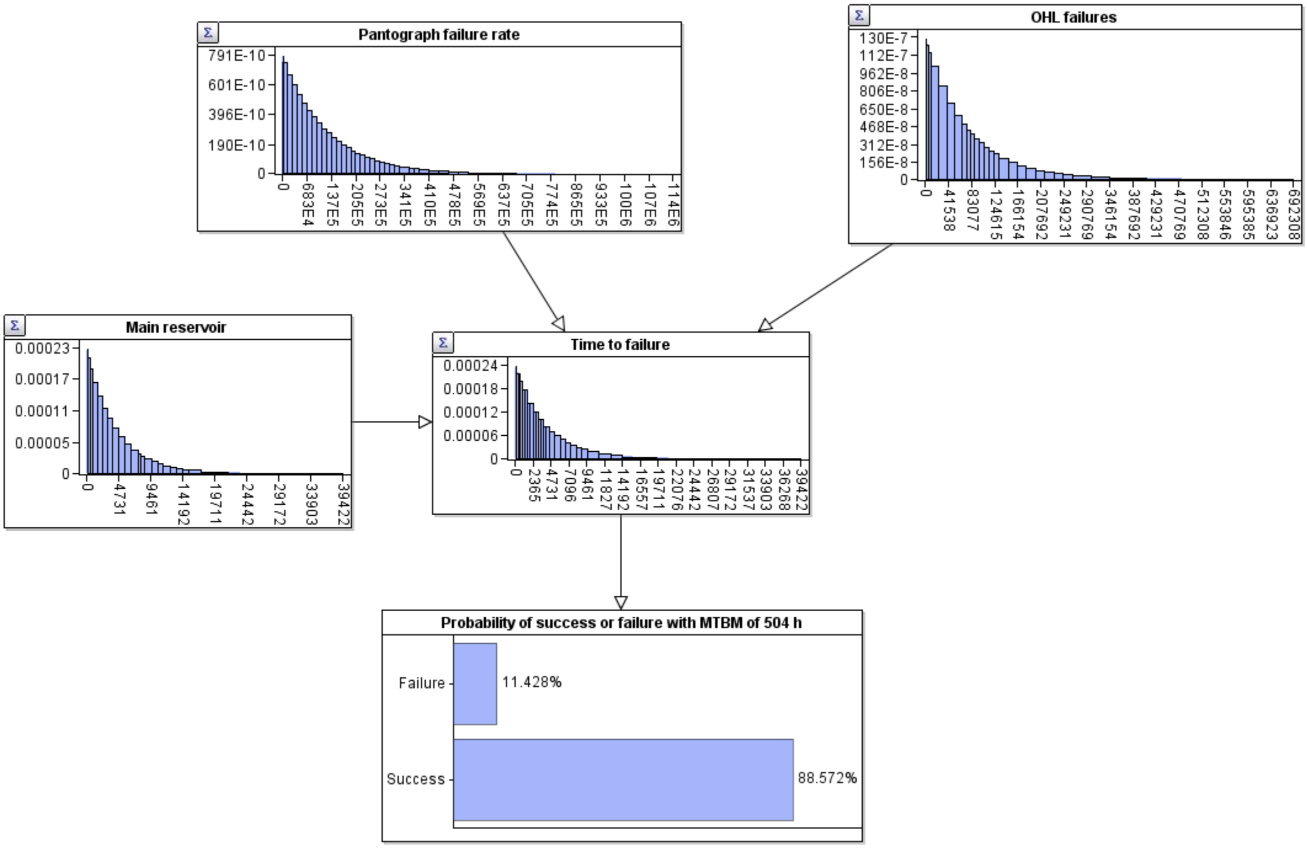

FIGURE 6. DBD structure and simulated results for probability of failure of pantograph.

TABLE 5. Prediction performance of GPR relative to that of other ML techniques.

ML	RMSE	MAE
GPR	1.693	1.428
SVR	1.975	1.539
MLR	1.866	1.665

TABLE 6. Estimated carbon strip wear loss with MTBM of 504 h.

Parameters	Values
Predicted wear	9.68 mm
Average travel distance for predicted wear	11,160.23 km
Projected maximum travel distance per day	280 km
Travel distance for MTBM of 504 h (equivalent to 28 days)	7,840 km
Predicted maximum wear loss for MTBM of 504 h	6.80 mm

that were identified. Second, FTA was performed to establish the pantograph subsystem's overall failure rate as well as to identify the logical connection between the top failure event (pantograph fault) and basic events (associated FMs). In Table 3, basic symbols indicate the link to the corresponding basic events. The number of parts refers to the number of components installed in the pantograph subsystems connected in series, which are connected by an OR-gate to the top failure event. The part failure rates for FMs related to the same component are the same. Based on the FTA shown in Fig. 5, the overall pantograph subsystem failure rate was estimated as 7.91×10^{-8} per hour (equivalent to 12.6 failures per million hours).

2) IMPACT OF MULTIPLE INTERFACE SUBSYSTEM FAILURES (OHL AND MR) ON PANTOGRAPH SUBSYSTEM

Although the FTA shown in Fig. 5 predicted a steady-state failure rate of 12.6 failures per million hours for the pantograph, it did not include the interface effects of other pantograph subsystems. For example, the primary reservoir can cause pantograph failure through lack of pneumatic air supply. Moreover, the OHL can cause pantograph failure through excessive current supply, owing to excessive vibrations, arcing, or flashovers. Therefore, for effective decision-making regarding an appropriate maintenance strategy and

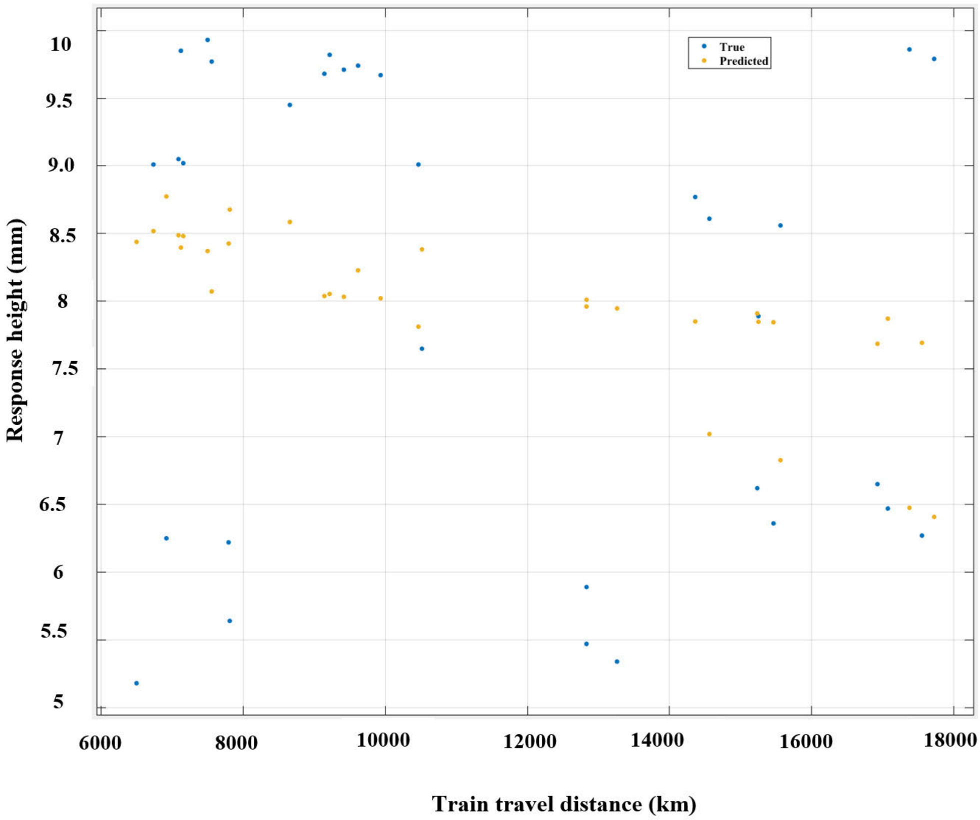

FIGURE 7. Carbon strip wear prediction training model.

frequency of implementation, the probability of failure owing to the effects of multiple interface subsystems on the pantograph must be determined. Considering the operator's desired MTBM of 504 h, prior node probability tables (NPT), including the node types, were defined as shown in Table 4. There were three continuous nodes, all of which are expressed as exponential distribution functions. The continuous nodes were the overall predicted failure rates from the FTA, MR, and overhead line. In addition, two synthetic nodes were introduced to support the simulation - discrete TTF node, a Boolean based on the impact of the failure of either the MR or the OHL, and the predicted probability of failure or success of the pantograph in the expected MTBM of 504 h. Fig. 6 shows the layout of the BN structure to support the DBD analysis. Each node contains an NPT, as specified in Table 4. By using (4)-(7) with 50 iterations, the probability of success was estimated as 88.572%, while the probability of failure of the pantograph owing to multiple interface subsystems (MR and OHL) was predicted as 11.428%. Therefore, considering the predicted probability of failure of 11.428%, we can expect at least 14.1 failures per million hours compared to the initial FTA steady-state prediction of 12.6 failures per million hours as noted in Section 3.2.1.

3) CARBON STRIP WEAR LOSS PREDICTION USING GPR

To predict the carbon strip wear loss, the GPR model with the SE function kernel given by (11) was used to build a predictive training model using the carbon strip training wear data from Table 2. To prevent overfitting and improve the prediction accuracy, five-fold cross-validation was performed using the training data. Fig. 7 shows the output of the carbon strip prediction model. It is anticipated that the irregular wear patterns may correlate to non-linear environmental conditions, including the vibration of the OHL, wheel and track alignment, and weather patterns. The performance of the prediction training model was validated in comparison with that of other ML techniques using (13)-(14), as shown in Table 5. The GPR model had smaller RMSE and MAE values than those achieved with GPR and MLR models. The prediction model shown in Fig. 7 was used to predict the maximum carbon strip wear loss using the test data shown in Table 2. The carbon strip wear loss prediction results indicated a maximum wear loss of ~9.68 mm in height, as shown in Fig. 8. The predicted results indicated that the pantograph carbon strip could be expected to experience a wear loss of ~6.80 mm during the operator's proposed MTBM of 504 h, as shown in Table 6, under the assumption of no premature failures owing to fractures and cracks. Based on the predicted wear rate, the pantograph can be expected to last no more than two 504-h inspection periods (MTBM) with 6.4 mm of the carbon strip remaining. In other words, ~2.4 mm of useful carbon strip may be wasted if it were to be replaced during this period. However, it provides an additional safety margin (buffer) from the legal disposable wear limit of 4 mm.

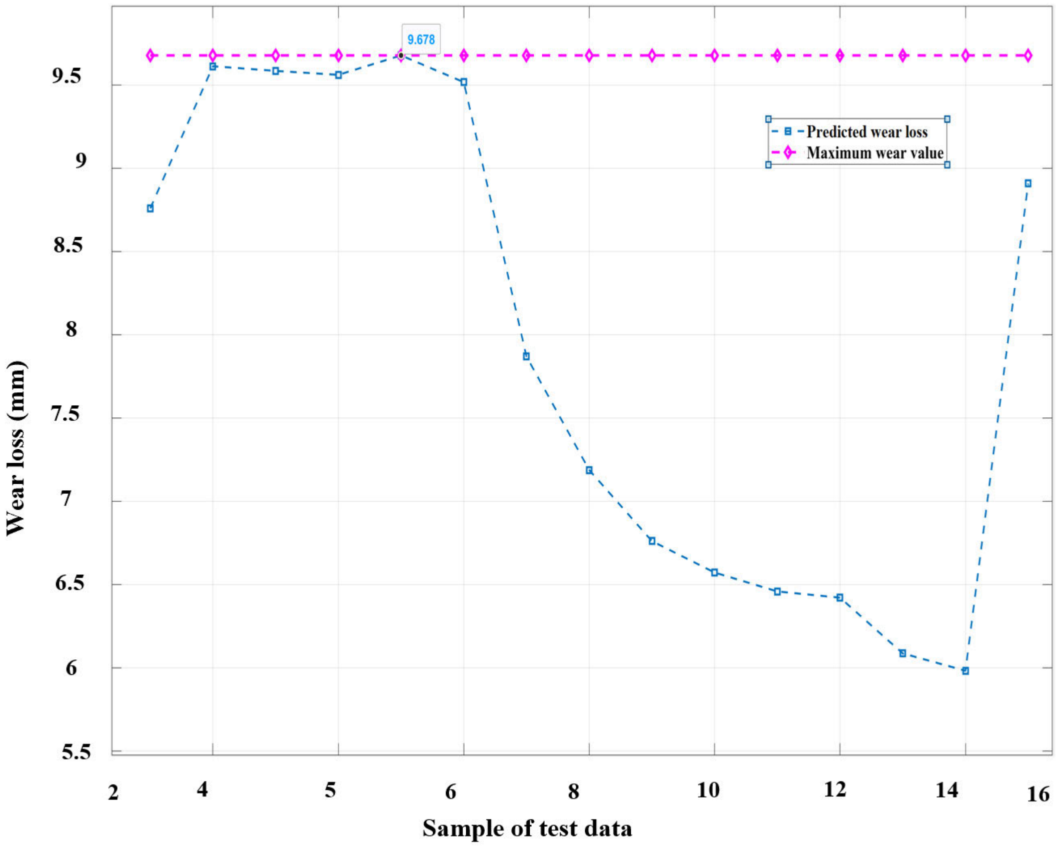

FIGURE 8. Carbon strip wear prediction using test data.

TABLE 7. Prior NPTS for quantitative analysis.

NPT	Data	Prior probabilities	Node type
Pantograph (PAN)	7.91×10^{-8}	(Ps = 0.999, Pf = 0.001)	Discrete node
Main reservoir failure (MR)	2.28×10^{-4}	(Ps = 0.891, Pf = 0.109)	Discrete node
Overhead line failure (OHL)	5.7×10^{-5}	(Ps = 0.972, Pf = 0.028)	Discrete node
Maintenance error	(Inexperienced, Experienced)	(0.745, 0.255)	Discrete node
Severity (0 ≤ penalty ≤ 5) (S1)	0 ≤ penalty ≤ 5	Uniform distribution	Simulation (continuous interval)
Severity (penalty ≥ 5) (S2)	penalty ≥ 5	Uniform distribution	Simulation (continuous interval)
Overall severity	(S1, S2)	Uniform distribution	Simulation (continuous interval)
Pantograph status (synthetic nodes)	Boolean	If statement depending on input selected probabilities	Simulated
Combined failure frequency (synthetic node)	1 (very unlikely) to 6 (frequent)	(0, 0.067, 0.13, 0.20, 0.267, 0.33)	Discrete nodes

4) OVERALL QUANTITATIVE RISK (LOSS OF FLEET AVAILABILITY) OWING TO PROPOSED INCREASE IN OPERATION PERIOD

To propose an appropriate maintenance strategy, it is imperative to understand the overall impact of pantograph subsystem failure on fleet availability (overall risk) during the proposed increase in operation period. The overall risk was evaluated quantitatively from four failure sources: maintenance error, pantograph, OHL, and MR (air tank) failure rates. Two severities in terms of penalty charges as uniform distribution functions were considered (up to five and more than five). The NPTs for the maintenance error, pantograph, OHL, and MR were estimated as shown in Table 7 by assuming an exponential function for the probability of failures and IID (i.e., probability of success $P_s = e^{-\lambda t}$ and probability of failure $P_f = 1 - e^{-\lambda t}$ with MTBM of 504 h). Four new synthetic nodes—combined failure frequency NPT, overall severity NPT, pantograph status NPT, and combined unavailability NPT—were introduced as part of the BFE modelling, as shown in Fig. 9. By using (17) with 50 iterations, the marginal probability distribution for the combined unavailability of the train owing to events and failures other than

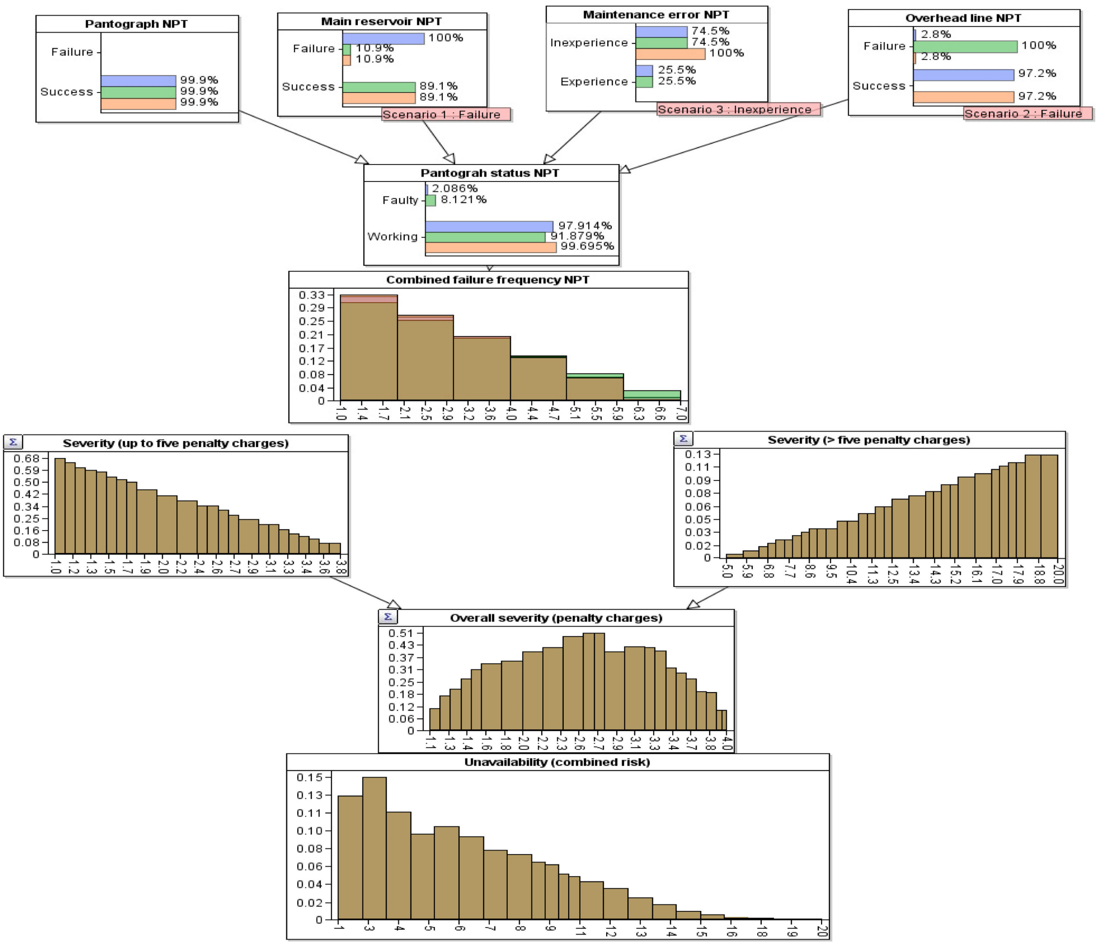

FIGURE 9. Overall loss of availability owing to proposed increase in operation hours.

TABLE 8. Results of expected overall risk (fleet unavailability) owing to pantograph subsystem failure.

Scenarios	Probability of failure (occurrence of events)	Predicted number of penalty payments (mean)	99th percentile range
1	MR	6.03	(3.12-8.38)
2	OHL failure	5.23	(2.21-7.34)
3	Inexperienced technician	6.91	(3.42-9.07)

pantograph failures are shown in Table 7 and Fig. 10 for three scenarios: (1) primary reservoir failure, (2) OHL failure, and (3) inexperienced maintenance error. Table 8 indicates that the maintenance error probability had the highest likelihood of fleet unavailability of ~7, followed by the MR with 6 and OHL with ~5. Table 8 shows the corresponding 99th percentile interval.

5) IMPLICATION OF RESULTS ON MAINTENANCE INSPECTION AND DECISION-MAKING

The FMECA analysis identified the carbon strip as a critical component of the pantograph due to its combination of high RPN and low maintenance interval (3,000 km), thereby indicating that it would need regular interventions to prevent failure. FTA predicted a low overall failure rate of 12.6 failures per million hours for the pantograph; however, the multiple failures caused by other external interface subsystems (OHL and MR) significantly increased the failure rate by 11.48%, which then corresponds to 14.1 failures per million hours. A further analysis of the carbon strip, a critical component, indicated that it could last two maintenance inspection periods (with a travel distance of 7,840 km) with a residual length of 2.4 mm in addition to the legal wear limit of 4 mm. Despite the predicted low failure rate and estimated wear loss, the proposed increase in the mission profile could affect the fleet unavailability because of multiple risk sources: maintenance errors, MR, and OHL failures. The carbon strip can last for the proposed mission profile of 504 hours even under the impact of multiple external and interface subsystem failures.

Owing to the impact of multiple interface issues and wear loss, there is a high probability that the intended extension from 14 h to 18 h can lead to unnecessary fleet unavailability of at least six fleets. The results of the present study indicate that to avoid this problem, the mission profile would be most realistic if a 2 h increase (i.e., from 14 h to 16 h) was implemented instead, equivalent to a travel distance of 4,480 km and a corresponding MTBM of 448 h. The proposed MTBM can lead to a more balanced and aligned maintenance strategy for all remaining components (also offering a good balance between safety and fleet availability), including the pantograph subsystems, as shown in Table 3.

IV. CONCLUSION

This study proposes a novel composite hybrid framework that seamlessly combines several independent hybrid models for performing a comprehensive through-life dependability analysis of complex engineering systems in consideration of their failures, reliability, maintenance, and risk. The first hybrid model (consisting of FMECA and FTA) can be applied at any stage of the asset life cycle, including design, operation, and overhaul, for conducting detailed steady-state subsystem analyses. The second hybrid model uses DBD for failure analysis of complex systems, consisting of multiple inter-dependent subsystems that share a common interface via direct or indirect functional and physical interactions. It can be applied at any stage of the asset life cycle, owing to its ability to combine qualitative and quantitative failure data to determine the probability of failure between inter-dependent subsystems. The third hybrid model uses GPR with a SE kernel for analysing the components of complex systems that are subjected to wear loss, fatigue, and cracks. It establishes the maximum wear loss, particularly during the operation, maintenance, and overhaul phases of the asset life cycle. The fourth hybrid model uses BFE with a Bayesian ML technique and n-fold convolutions to quantitatively determine the overall risk of the complex system. It determines the overall marginal probability of risk posed by the many interactions from external and internal factors that can lead to the subsystem's failure that in turn might lead to unavailability and accidents.

The aggregated risk allows for a measured approach in strategic decision-making related to the risk of subsystem failure for operational effectiveness. The output of this composite hybrid framework can support effective decision-making for complex engineering systems across multiple life cycle stages. The proposed model was validated through a case study of a train operator, and the results were used to recommend an alternative operating period of 16 h instead of the operator's proposed period of 18 h. Owing to the effect of multiple interactions and dependencies that are often embedded within complex engineering systems, the proposed composite hybrid framework can be a useful tool for failure and dependability analysis. Although this framework is practical and efficient for failure analysis and decision-making, it could be improved in the future via automation to enhance the data processing and computation of discrete and continuous variables.

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