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Risk-Informed Support Vector Machine Regression Model for Component Replacement–A Case Study of Railway Flange Lubricator

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ABSTRACT The railway-rolling stock wheel flange lubricator protects the wheels and railhead by lubricating their contacts. Failed or missing flange lubricators can lead to excessive wheel wear, wheel flats, wheel cracks, rolling contact fatigue, rail damage, and derailment accidents. In extreme cases, missing or worn flange lubricators due to nonlinear rail conditions may lead to fire hazards, particularly in underground rail infrastructure. In addition, the location of lubricators present accessibility issues and prolong the diagnosis of failure. This study therefore proposes an adaptive risk-based support vector regression (SVR) machine with a Gaussian kernel function that can accurately and proactively predict the wear loss of flange lubricators from a small data set. While most flange lubricators fail owing to wear loss, others fail owing to premature failure modes such as cracks and fatigue. The risk-informed feature evaluates failure rates associated with failures other than wear loss to support a balanced determination of the optimised replacement frequency. The proposed model was applied and validated as a case study for the London underground train. The findings showed that the optimised maintenance inspection of the flange lubricator, as a balance between safety and organisational resource constraints, was an average of every 4000 km between train operations.

INDEX TERMS Railway, wheel flange lubricator, wear, support vector regression, derailment.

I. INTRODUCTION

In the transportation of goods and passengers, railways play an important role. Over 210,000 people work in the UK rail transport sector, including in the supply chain, producing GBP 9.3 billion of gross domestic product (GDP) per year [1]. In order to accommodate passengers, need for improved comfort and shorter travel times, there have been major developments in speed, axle loads, train length, and rail line traffic density over the past few years. This has resulted in increased risks to rail operations owing to rolling contact fatigue (RCF) and rail wear due to flange lubrication failure [2]. Therefore, flange lubricators play a critical role in reducing excessive wheel slips and damage to the railheads. According to a six-year dataset from the Federal Railroad Administration [3], defects related to flange lubricators such as track-train interaction, buckled track, broken rails, welds due to excessive friction, and broken wheels due to wheel flats and cracks are responsible for as many as 17% of derailment cases [3]. In addition, the UK Rail Accident Investigating Branch (RAIB) confirmed that the derailment that occurred in Epsom in 2006 between Raynes Park and Epsom line was due to rapid side wear owing to a lack of rail and flange lubrication [4]. Despite the critical role of flange lubricators against rail accidents, these lubricators are mostly reactively maintained and replaced as part of the wheel assembly inspection, which far exceeds the functional life of the flange lubricators [3], [4]. In addition, the complicated position of the flange lubricators at the inner space between the axle and wheel renders them difficult to inspect adequately, other than through the pit-stop train facility that provides sufficient access to the maintenance crews under the train. In most cases, the flange lubricators could be worn out prior to the inspection, causing lasting damage to expensive wheels and railheads and may even lead to worst-case scenarios such as derailment and fire.

For active wheel-rail contacts, the nonlinear environmental and external conditions such as changing weather patterns;

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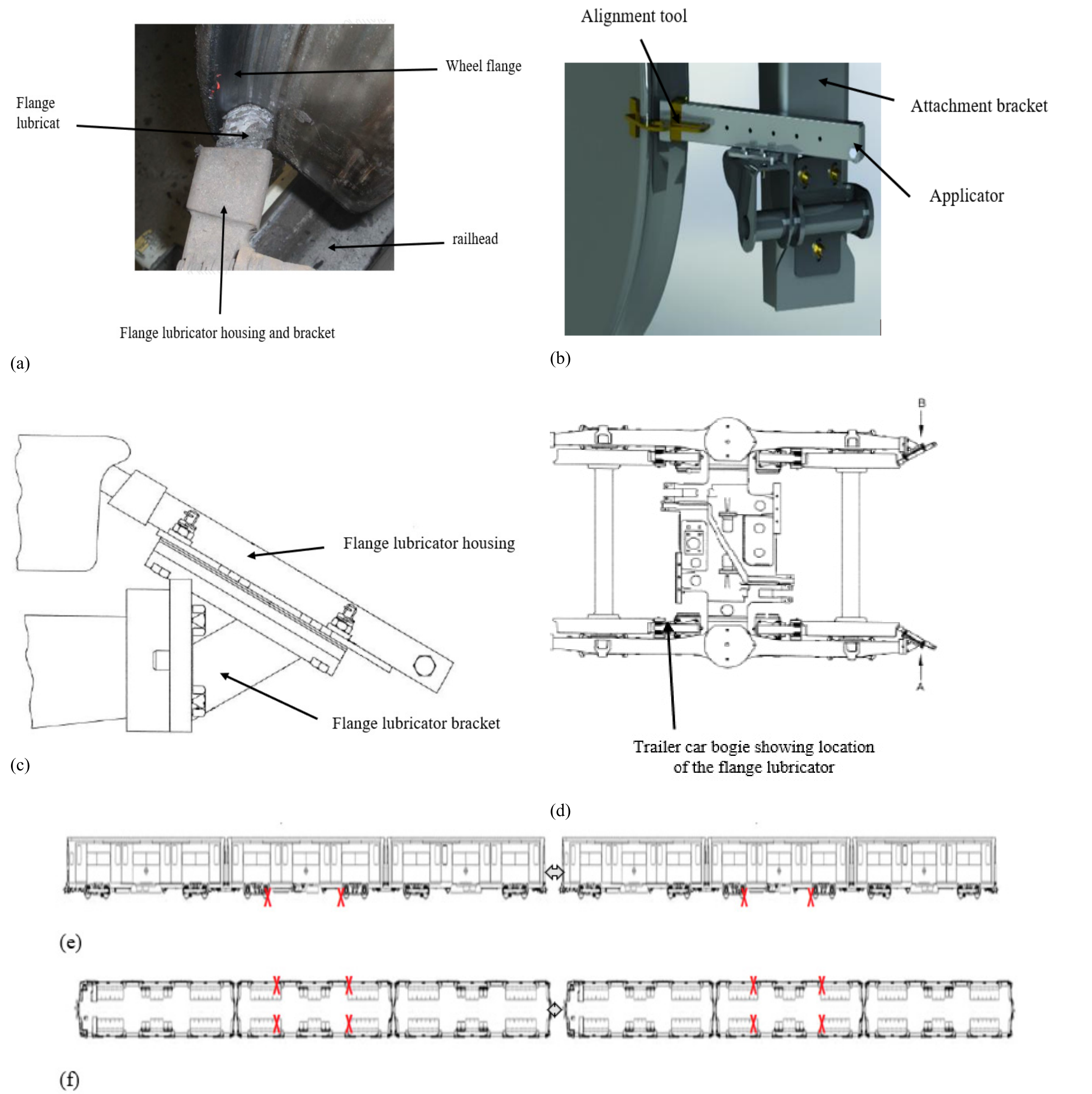

FIGURE 1. Underframe of fleet layout with flange lubricators (a) Illustration of flange lubricators at wheel contact. (b) Active wheel and flange contacts. (c) Detail of the lubricator housing assembly. (d) Location of the lubricator underneath the trailer bogie. (e) Location from the sideview on a trailer car of a six-car train and (f) location underneath a trailer of a six-car train [9], [10].

driver errors relating to indiscriminate acceleration and braking; tube dust; and leaves on the lines; significantly affect the friction coefficient which in turn contributes to erratic and excessive wear losses on the flange lubricators. Flange lubricators, including housing and brackets, can also be susceptible to premature failure modes such as cracks and fatigue, often leading to leading to loss of lubrication between wheel and rail. Figure 1 illustrates an example of flange lubricators, housing assembly, brackets, and their locations on a rolling stock vehicle. While several experimental studies have been conducted to evaluate and analyse the different material contents of wheel and rail lubricators, few have considered the efficacy of an appropriate maintenance replacement or inspection plan as an intervention strategy that allows preservation of the flange lubricators [5]–[7]. Although the probability of failure of the flange lube can be difficult to predict owing to multiple failure mechanisms, the consequence of failure can lead to derailment and/or catastrophic incidences involving multiple casualties. The intricate location of the flange lubricator complicates proactive maintenance and data collection. In addition, time, punctuality, and dynamic train operating schedules require a dynamic technique that can support an adequate failure analysis without compromising service operation [8].

Recently, researchers have been interested in the applications of machine learning techniques, including neural network and nonlinear regression models, to analyse mechanical wear systems [11]–[18]. While the neural network may be susceptible to chance effects, it is possible to overtrain a network, which can have an impact on accuracy due to incorrect interpretation [19], [20]. However, machine learning regression models such as support vector regression (SVR), Gaussian mixture regression (GMR), and Gaussian process regression (GPR) have been criticised for their accuracy and computational costs [19]–[24]. For nonlinear prediction such as wear loss, GPR uses all the data points in the objective function and hyperparameters to ensure accuracy of prediction, whereas GMR generates a new set of data points centred on the Gaussian function to maintain accuracy [19]–[25]. On the contrary, SVR uses a subset of data points called support vectors to maintain the accuracy of the prediction model [19]–[25]. Therefore, SVR uses less data points than the GMR and GPR to ensure accuracy of the wheel prediction [19]–[21], [26]. Owing to the location of the flange lubricators in trailer cars (for example, in the UK there are two trailer cars per six-car rolling stock vehicle and one per five or three car vehicles), datapoints can be limited; therefore, SVR can utilised to provide a better prediction than the GPR and GMR. The accuracy of the SVR model depends on the settings of the hyperparameters and constraint-based optimisation, such as the particle filter swarm optimisation, genetic algorithm, simulated annealing, and k-fold cross-validation techniques [27]–[31]. Once the values of the SVR parameters have been established by these optimisation methods, the training model can be deployed to predict the test data without taking into consideration the new hyperparameters generated from new sets of data, leading to inaccurate predictions [21], [26]. Despite the generalised wear loss, flange lubricators can suffer from premature failures from other failure modes such as cracks, fatigues, and human error conditions. Therefore, maintenance predictions based on SVR wear loss alone cannot be entirely accurate.

II. THE OPTIMISATION TECHNIQUE

Different optimisation techniques exist for system and performance data analysis, including classical-gradient descent-based, dynamic programming, mixed-integer, nonlinear programming, and constrained and unconstrained methods [32]. Given that most of the optimisation methods usually focus on functional parameters and their derivatives to provide a view of specific system optimisation functions, any inaccuracy in the functional parameters impedes the accuracy of the results [32]. Unfortunately, the complex behaviour of the railway infrastructure, including nonlinear failure patterns, intricate dependencies, and challenging environments can hardly be captured by explicit analytical models. Genetic algorithms with modern numerical search techniques have been developed and implemented for optimisation in many engineering projects and life science studies because of their global reach and flexibility [19], [20], [33]. However, the non-reliance on the operation context of the system for optimisation poses a limitation to accuracy and correctness and representativeness, especially in the railway industry, where various differential topographical, environmental, and weight factors exist [34]–[36].

To optimise the maintenance interval inspection with respect to the safety of a critical component such as the flange lubricator, multi-layered optimisation using the wear degradation and failure threshold was adopted [37]. The wear loss analysis was directly focused on the flange lubricator, thereby eliminating the bias of tolerances that may exist in the functional parameters. In addition, the failure threshold considers other failure modes of the flange lubricator that are not directly associated with wear loss. The combined technique aims to improve the accuracy of determining the remaining useful life (RUL) and allows proactive, holistic, dynamic, and risk-informed optimisation inspection, characterised by low probability of derailment and expenditure. Furthermore, RUL_i can be expressed as $EOL_i - CT_i$, where EOL_i (end of life) is the point where a flange lubricator can still operate but does not meet functional requirements as determined by the estimated failure threshold and CT_i is the current time predicted from the wear loss model, as shown in Figure 2 [37].

Non-destructive testing (NDT) is the formulation and implementation of technical methods to analyse materials or components without compromising their potential utility, integrity and serviceability. NDT is used to identify, locate, calculate, and evaluate defects. NDT is also used to measure geometrical characteristics as well as assess integrity, properties, and structure [38]. Structural health monitoring (SHM) and different types of NDTs have been utilised to examine and evaluate the remaining useful life (RUL) of composite structures such as flange lubricator [39], [40]. NDT is capable of offering an ideal combination of quality management and cost efficiency during manufacturing, by enabling testing of parts without interfering with the final application of the product. Despite the availability of a variety of SHM and NDT techniques for identifying damage in composite materials, no single approach has proven to be proficient for identifying damage associated with all life cycle stages (i.e. design, manufacturing, operation, maintenance, etc) [39], [40]. Additionally, using SHM and NDT techniques for a non-repairable composite item such as a flange lubricator during in-service operation can pose several challenges to cost effectiveness, impact damage, and lapsed time [41]. Also, accessibility challenges posed by the location of the flange lubricator can negatively impact the effective utilisation of NDT and SHM approaches such as infrared thermography for the detection and evaluation of defects in flange lubricators [42]. Sensors, data transmission, data integrity, and analytic modules for translating data into useful information for both the track and the rolling stock vehicle are needed for SHM and remote

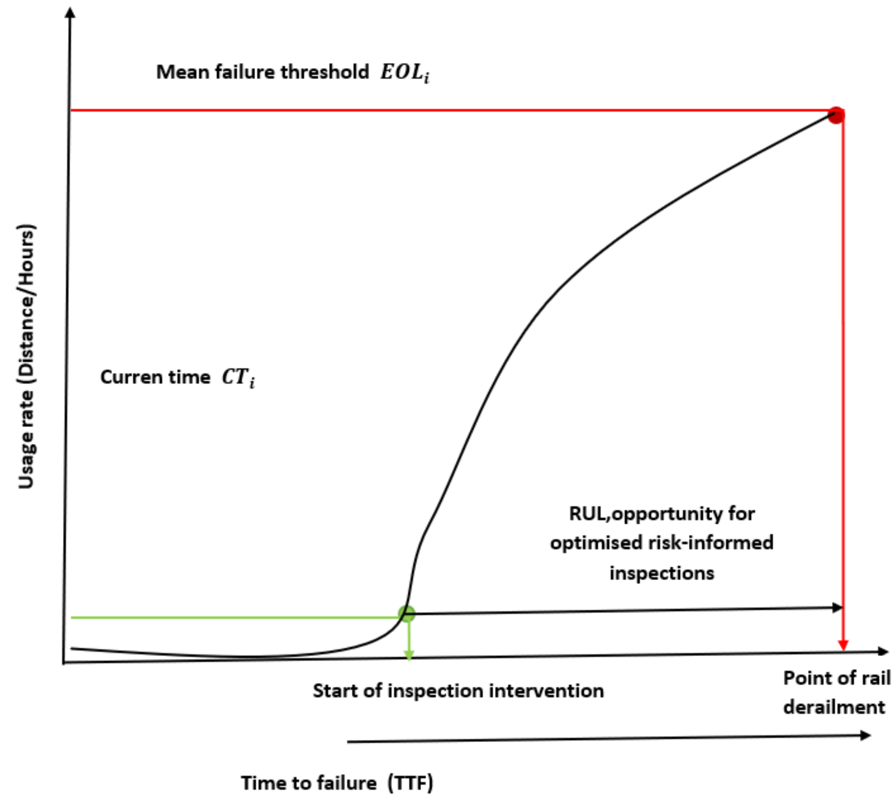

FIGURE 2. Illustration of the relationship between RUL, CT, and EOL [33].

condition monitoring systems [43], [44]. The cost of supporting new inspection and automated SHM technology capability across the UK network has been estimated at £100 million, while the annual ongoing maintenance cost for UK network rail has been estimated at £4.5 billion for Control Period (CP) 5 (2013-2019) [45].

In this study, a novel SVR with a Weibull failure threshold that allows adaptive updating of the hyper-parameters whenever new data becomes available, thereby offering a dynamic failure threshold prediction that is based on premature failure modes of the flange lubricator before reaching the legal disposal limits is proposed. Because the flange lube experienced nonlinear internal and external failure patterns in addition to error conditions, the Gaussian kernel function capable of addressing the nonlinearity of continuous predictive functions has been considered. With this method, CT_i corresponds to the SVR wear loss and the EOL_i is evaluated as the Weibull mean time-to-failure threshold. The remainder of the paper is organised as follows: Section 3 introduces the proposed method. The case study from which illustrative data sets were acquired is described in Sections 4, and 5 respectively provide the study findings and conclusions.

III. PROPOSED SVR WITH WEIBULL TIME-TO-FAILURE METHOD

The new adaptive method combines ε–SVR with Weibull mean time-to-failure as a threshold parameter to propose a risk-based inspection interval for the flange lubricators. To predict the output wear loss and eventually the risk-based inspection intervals with the test data ($Tt - 1$), the SVR parameter optimisation with the training data ($Tr - 2$) is first estimated with the input measurement data ($M - 2$). Concurrently, the mean time-to-failure threshold for other premature failures, other than those due to wear loss for test data $Tt - 1$, is estimated, as shown in Figure 3. To reduce the risk of derailment caused by the failure of the flange lubricator, the recommended risk-based inspection intervals based on the predicted wear losses cannot exceed the mean time-to-failure threshold. The model consists of a wear prediction step and an updating step, making it an adaptive system. During the prediction step, historical data measurements from 1 to $M - 2$ influence the estimation of the SVR parameters. Upon collection of the new measurement data ($M - 1$), the ε SVR parameters, including the training data $Tr - 1$, are iterated and updated for a new prediction based on the new test data ($Tt - 1$). Output wear losses and options for risk-based inspections are established using $Tt - 1$. The new mean time-to-failure threshold is updated based on the overall historical data from $Tt - 2$ to $Tt - 1$ (new current data). Risk-based inspections from the predicted wear losses are compared and evaluated against the benchmark mean time-to-failure for premature failures to establish an optimised risk-based inspection schedule capable of averting the risk of train incidents and accidents such as derailment and fire. The iteration continues with new input

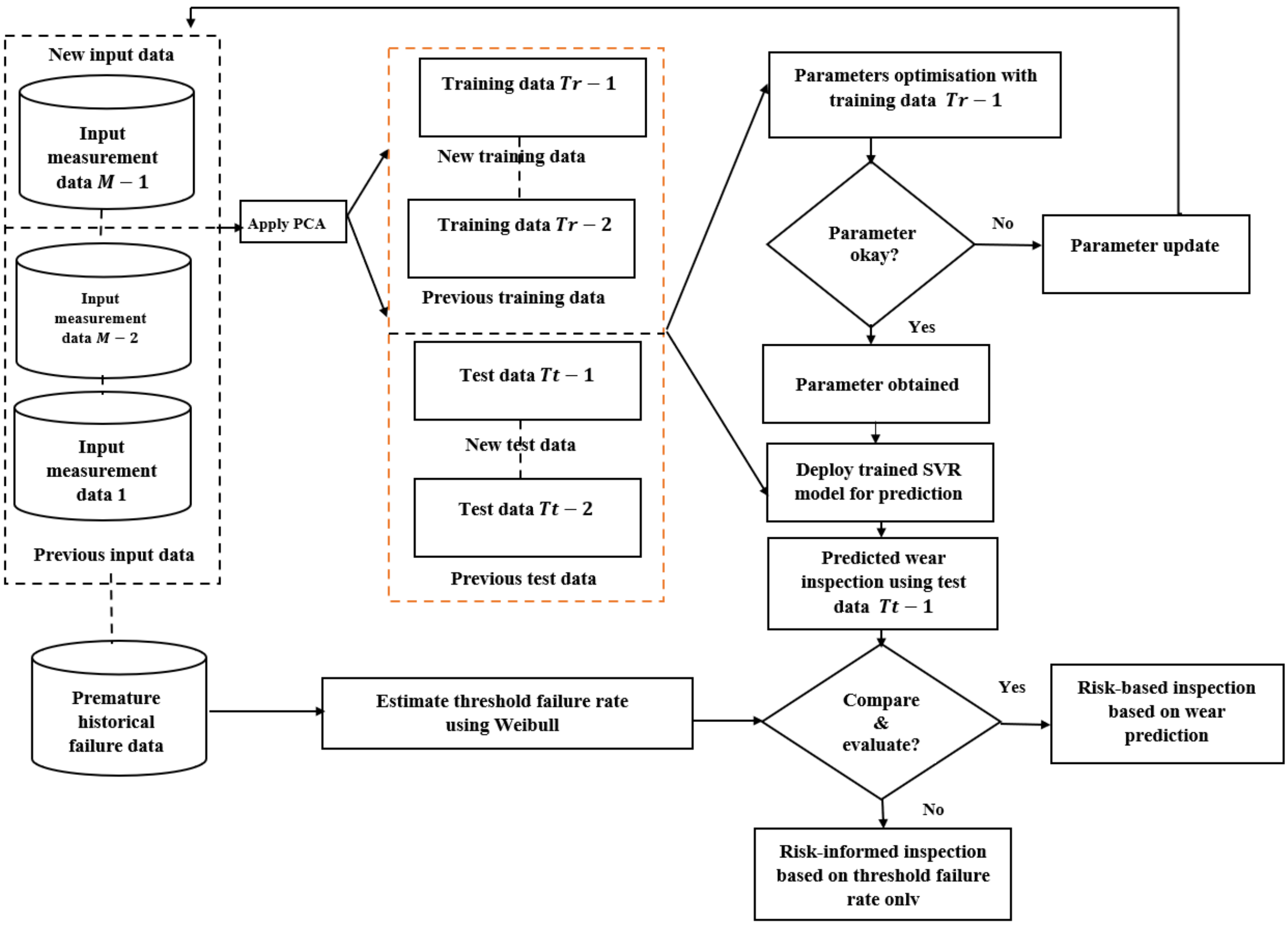

FIGURE 3. **SVR with time-to-failure model.**

measurement data and historical premature failure caused by other failure modes, as shown in Figure 3. As is often the case with most data-intensive approaches, the availability of more data enriches the historical database, which in turn improves the accuracy and representativeness of the model's outcomes. While the addition of new data to existing measurement data is anticipated to improve accuracy of prediction over time, it must be noted that precision will also depend on whether the input measurement data for the flange lubricator represents the operational context as well as the environment in which the asset operates. Additionally, as the historical database grows in size, the possibilities of data variance, noise, uncertainty and misclassification also grows which may impede overall representativeness of outcomes. Therefore, simple but effective linear classifiers such as principal component analysis (PCA) [44] can be incorporated to reduce data dimensionality as well as accommodate noise, human error, uncertainties and variance in historical data from measurement data sets for multivariate regression analysis models, such as the risk-informed model. Collinearity between predictor variables is handled using PCA [46]. PCA regresses the response on the uncorrelated linear combinations of the input variables (i.e., from the uncertainties) that best describe input space variability. Because these predictor variables are orthogonal, we can ignore the collinearity issue of linear combinations with low variability explanation power [47], [48]. The PCA is an orthogonal transformation that transforms data to a new coordinate system by selecting the variable with the greatest variance and scalar projection of the data on the first coordinate and the second greatest variance by projection on the second coordinate. With the training data $(Tt - 1)$ and predicted vector u_n, projected data with the mean as $u_1^T\ (Tt-1)\,u$ and $u_1^T\overline{(Tt-1)}u$ can be defined with the variance of projection as [48], [49]:

$$= \frac{1}{N}\sum_{i=1}^{n}\left(u_1^T\ (Tt-1)\,u - u_1^T\overline{(Tt-1)}u\right)^2 \qquad (1)$$

The primary goal of PCA is to find the vector that maximises variance by reducing estimated score uncertainties in data measurements from first to ith measurement data by considering one-dimensional reduction as shown in [48], [49]:

$$Max = \frac{u_1^T}{N}\sum_{i=1}^{n}\left((Tt-1)\,u - \overline{(Tt-1)}u\right)^2 \qquad (2)$$

Other methods for estimating model uncertainty, such as ordinary least squares (OLS), ridge regression (RR), and partial least squares (PLS), can also be used [48].

A. SUPERVISED SVR WEAR LOSS PREDICTION WITH THRESHOLD FAILURE METHOD

A support vector machine (SVM) was first proposed by Vapnik [50] and is based on a structured risk minimisation principle, where the aim is to minimise the upper bound of the generalisation error for an error-based probability technique rather than finding and lighting the empirical errors [50], [51]. SVM is mostly applied in binary classification problems. In contrast, the SVR, which is an extension of the SVM, can output a response variable in the continuous spectrum for regression problems [50], [51]. Given a set of training data $M = \{(x_i, m_i)\}_{i=1}^{R}$, where x_i is the input vector and with m_i the actual output value. Furthermore, R is the total number of data points and assuming a linear function f, the linear regression function can be formulated as follows [28], [50], [51]:

$$y = f(x) = w^T x + b \tag{3}$$

where w and b are coefficients of the weight vector and hyperplane bias of the model, respectively. For nonlinear cases such as a flange lubricator wear loss, the low-dimensional input vectors can be mapped via a nonlinear function $\psi : Z^d \rightarrow R$, where R is a feature space of ψ. The nonlinear regression function after mapping becomes:

$$y = f(x) = w^T \psi x + b \tag{4}$$

where the coefficients w and b can be obtained via minimisation and optimisation following the regularised risk functions:

$$r(C) = C\frac{1}{M}\sum_{i=1}^{M} \Gamma_\varepsilon \left(m_{i,}y_i\right) + \frac{1}{2}\|w\|^2 \tag{5}$$

where,

$$\Gamma_\varepsilon(m, y) = \begin{cases} 0 & if\ |\text{m-y}| \leq \varepsilon \\ |\text{m-y}| - \varepsilon & otherwise \end{cases} \tag{6}$$

Above, C and ε are trade-off and penalty parameters, respectively. With the introduction of the ε-insensitive loss function $\Gamma_\varepsilon(m, y)$ in Equation (5), the coefficient parameters w and b can be estimated by evaluating the convex optimisation. For example, the ε-insensitive loss equals zero if the forecasted value is within the ε-margin, as shown in Equation (6), which is a measure of the precision of the regression, while $\|w\|$ corresponds to the slope and Euclidean norm w, which is a measure of the flatness of the function y. Furthermore, C corresponds to the penalty parameter between the empirical risk and flatness of the model. By introducing two positive slack variables, ξ and ξ^*in feature space, as shown in Figure 4, which is an equal distance from the actual values to the corresponding boundary values of the ε-margin, Equation (5) can be transformed into the following constrained and minimised form [52].

$$r\left(w, \xi, \xi^*\right) = \frac{1}{2}\|w\|^2 + C\left(\sum_{i=1}^{M}\left(\xi_i + \xi_i^*\right)\right) \tag{7}$$

with the following constraints:

$$\begin{cases} w\psi(x_i) + b_i - m_i \leq \varepsilon + \xi_i^*, & \\ m_i - w\psi(x_i) - b_i \leq \varepsilon + \xi_i & i = 1, 2, \ldots, M \\ \xi_i,\ \xi_i^* \geq 0, & \end{cases}$$

The constrained optimisation problem in Equation (7) is addressed through the Lagrangian dual method, which presents a numerical prediction method to estimate the prediction value [48]:

$$\begin{aligned} &L\left(w, b, \xi, \xi^*, \alpha_i, \alpha_i^*, \beta_i, \beta_i^*\right) \\ &= \frac{1}{2}\|w\|^2 + C\left(\sum_{i=1}^{M}\left(\xi_i + \xi_i^*\right)\right) \\ &\quad - \sum_{i=1}^{M} \alpha_i \left[w\psi(x_i) + b_i - m_i + \varepsilon + \xi_i\right] \\ &\quad - \sum_{i=1}^{M} \alpha_i^* \left[m_i - w\psi(x_i) - b_i + \varepsilon + \xi_i^*\right] \\ &\quad - \sum_{i}^{M}\left(\beta_i\xi_i + \beta_i^*\xi_i^*\right) \end{aligned} \tag{8}$$

The Lagrange multipliers for each constraint, α_i and α_i^* are estimated with the optimal weight vector of the regression hyperplane, which gives the numerical SVR method nonlinear predictive function as:

$$f\left(x, \alpha_i, \alpha_i^*\right) = \sum_{i=1}^{M}\left(\alpha_i, \alpha_i^*\right) K(x, x_i) + b \tag{9}$$

where $K(x, x_i)$ is the kernel function and its value is the inner product of the two vectors x_i and x_j in the feature space $\psi(x_i)$ and $\psi\left(x_j\right)$. Any function that satisfies Mercer's condition can be used as the kernel function. The hyperplane bias, b, is estimated using the Karush–Kuhn–Tucker (KKT) conditions by converting the inequality constraints into an equation of the form $g(x) = 0$ by adding or subtracting the slack variables and then estimating the corresponding equality constrained optimisation problem [54], [55]. To ensure a high accuracy and accurate nonlinear wear loss prediction for the smaller sample data points for the flange lubricator, the Gaussian kernel, which is centred on each training datapoint, is considered as the kernel function in this study [53]:

$$K(x, x_i) = exp\left(-\frac{\sigma^2}{2}\left|x_i - x_j\right|^2\right) \tag{10}$$

Other common kernel functions, such as linear functions and polynomial functions, can be considered depending on the severity of the nonlinearity of data [55]. The predictive performance of the model was obtained with the least root mean squared error (RMSE) and mean absolute error (MAE), as shown as in Equations (11) and (12) [56].

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\lfloor f(x_i) - y_i\rfloor^2} \tag{11}$$

$$MAE = \frac{\sum_{i=1}^{N}\left(\lfloor f(x_i) - y_i\rfloor\right)}{N} \tag{12}$$

where $x_i, \ldots, x_N$ are the input wear data measurements and $f(x_i), \ldots, f(x_N)$ are the predicted output values by the SVR method. Furthermore, $y_i, \ldots, y_N$ are the measured wear

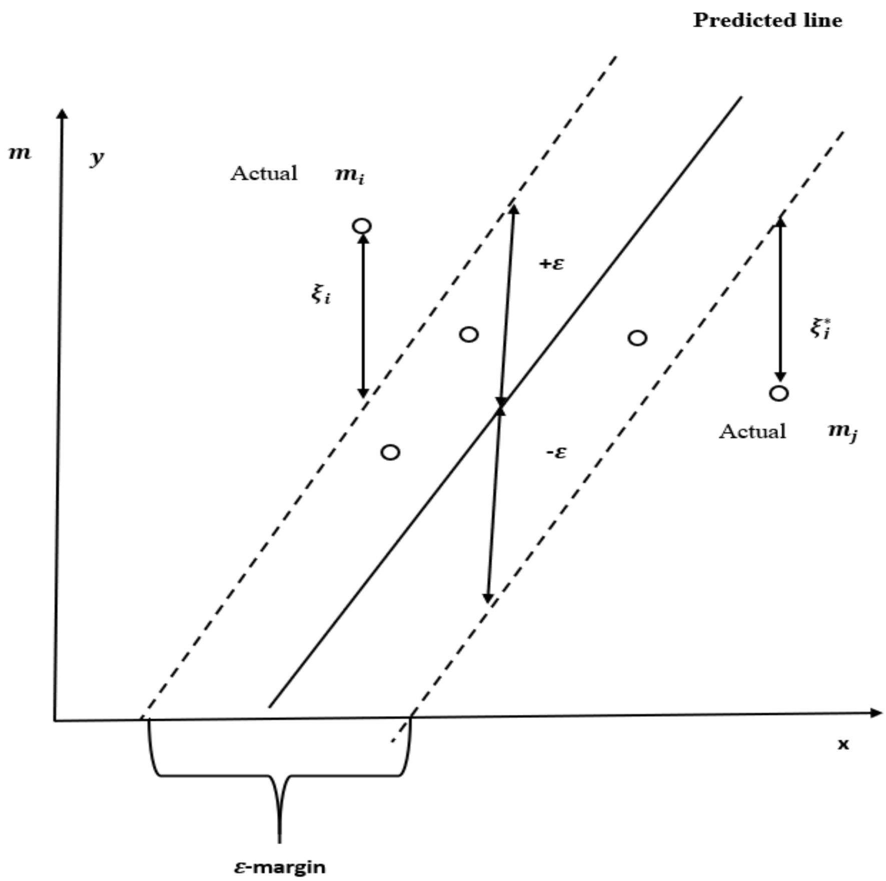

FIGURE 4. ε-insensitive loss function and parameters used for SVR [36].

losses from the test data and N is the number of samples in the tested data. The predicted wear loss with respect to the usage parameter P can be estimated as $f\left(x, \alpha_i, \alpha_i^*\right) \times P$, where P is either a distance or time measurement, depending on the context.

Following the wear prediction, the Weibull distribution, which is suitable and flexible for small sample mean-time-failure parameter prediction for premature failure modes such as fatigues and cracks can be estimated as follows [32], [57], [58]:

$$F\left(z_i\right) = 1 - exp\left[-\left(\frac{z_i}{\eta}\right)^{\beta}\right] \tag{13}$$

$$F\left(z_i\right) = 1 - exp\left[-\left(\frac{z_i - \gamma}{\eta}\right)^{\beta}\right] \tag{14}$$

where $z_i, \ldots, z_N$ are the input frequency of the failure caused by other failure modes, β is the shape parameter, η is the characteristic life, and γ is the location parameter or expected minimum life. The 2-parameter mean time-to-failure (Equation (13)) can be considered in the early stages of the prediction model, where limited historical test data are known. Where sufficient information about the time-to-failure caused by premature failures is known, the 3-parameter mean time-to-failure (Equation (14) can be considered for the estimation of the threshold mean-time-to failure.

B. OPTIMISED RISK-INFORMED INSPECTION ALGORITHM

Given a wear training data x, test wear data v, with a corresponding test failure history by other failure modes z, then the algorithm can be described as follows:

1. Initialise the function $f(x)$ in **Equation (4)**.
2. Apply PCA to **Equation (2)** to address uncertainties in input measurement data.
3. Compute the coefficient parameters and weight vectors, C and ε using the dual Lagrangian method in **Equation (6)**.
4. With the Gaussian Kernel, establish the parameter δ as given in **Equation (10)**.
5. Build a predictive SVR model with the established parameters in **Equation (9)**.
6. Iterate steps 2, 3, and 4 until a predefined stopping criterion is met.
7. With test data v, predict the new wear loss in **Equation (9)** and establish the risk-informed inspections options.

8. Evaluate and compare the SVR prediction model performance according to **Equations (11)** and **(12)**.
9. Compute failure threshold $F(z)$ using premature test failure data z using **Equations (13)** and **(14)**.
10. At completion, the failure threshold is set as the benchmark and the results are compared in steps 6 - 8.
11. If the inspection interval in step 5 is less than or equal to that in step 8, implement the risk-informed inspection options identified in step 6.
12. Else implement risk-informed inspection option in step 8.
13. With new training data x, update, repeat, and iterate steps 1 to step 12.
14. End.

IV. CASE STUDY EXAMPLE

The case study considers the prediction and forecasting of flange lubricator maintenance inspection for a UK-based mass rapid transit with a total of six carriages. Thus, there are four lubricators per compartment and twelve lubricators per six-car train. There are two flange lubricators for each lubricator stick. The training data were gathered using a digital weight scale of 10% total fleet size, which comprises 56 train distance measured in kilometres including weight wear measurement data points (in grams), as illustrated in columns one and two in Table 1, respectively over 18 months period. The average weight of the new flange lubricator is 106 g with a legal disposal limit of 5 g. In addition to the training data, 39 samples of test data were collected from an additional 6% of the fleet size, where 28 kilometres-to-failure data were recorded for the flange lubricator that failed by other failure modes such as cracks and fatigues, as shown in Table 1. MATLAB version R2020a and Isograph reliability workbench version 15 were used for the analysis.

The analysis began by developing and establishing hyperparameters and an SVR predicted model based on the 56 samples of training data. Eight-fold cross-validation was performed for the training and validation to prevent overfitting and to preserve prediction accuracy. In this study, the model hyperparameters were established by varying the number of training data to select the best hyperparameters based on RMSE and MAE, as shown in Table 2. The hyperparameters for the 56 training datasets were selected for the SVR predictive response model. The SVR model's performance decreased with a reduction in the training data. It can be observed in the response plot in Figure 5 that the SVR can provide better predictive performance for a small sample of random nonlinear wear values for the flange lubricator, compared to other machine learning techniques such as GPR and multiple linear regression (MLR), as shown in Table 3. The RMSE and MAE values of the SVR model were lower than those of the GPR and MLR.

Next, the predictive model in Figure 5 was used to predict the wear rate using the test data in column 3 of Table 1. As shown in Figure 6, the predicted average- and maximum wear for the flange lubricator were estimated to be approximately 9.91 and 12.34 g, respectively. While the predicted results indicated that most of the wear rates occurred close to the average wear, the maximum wear was selected to consider

TABLE 1. Train distance, flange wear measurements, and distance-to-failure data.

Train distance (km)	Training wear data (g)	Test wear data (g)	Premature distance-to-failure (km)
3893	13.50	14.00	4459
3879	13.50	19.00	4442
3846	13.50	14.50	4471
3923	17.50	13.00	4466
4241	6.00	5.00	4641
3937	4.00	17.00	4442
4415	13.50	22.00	4419
3939	17.50	12.00	4508
4063	4.00	2.00	4503
4150	3.00	4.00	4380
4472	4.00	9.00	4265
4370	14.00	4.00	4609
4321	2.00	16.00	4524
3926	19.00	11.00	4521
4065	18.00	1.00	4330
3888	10.00	19.00	4471
4043	19.50	14.00	4103
4320	19.50	20.00	4524
4160	15.50	19.20	4783
4056	11.50	2.00	4382
3883	4.00	18.50	4568
3859	16.00	4.00	4453
4074	4.00	16.00	4579
4353	8.00	10.00	4195
4385	11.50	5.00	4600
4109	11.50	2.00	3039
4254	11.50	18.50	3883
4057	9.50	18.00	3859
4160	6.00	6.00	
4032	10.00	16.50	
4165	10.00	5.00	
3896	6.00	1.00	
4519	8.00	11.00	
4031	14.00	18.00	
3878	14.00	11.00	
4112	16.00	2.00	
4073	10.00	15.00	
3857	5.00	14.00	
4373	2.00	14.00	
4103	2.00		
4161	2.00		
4134	1.00		
4088	13.00		
4124	12.00		
4238	2.00		
4225	4.00		
3845	9.00		
3864	4.00		
4493	16.00		
4365	11.00		
4490	1.00		
4260	16.00		
4147	7.00		
3982	8.00		
4522	11.00		
4285	4.00		

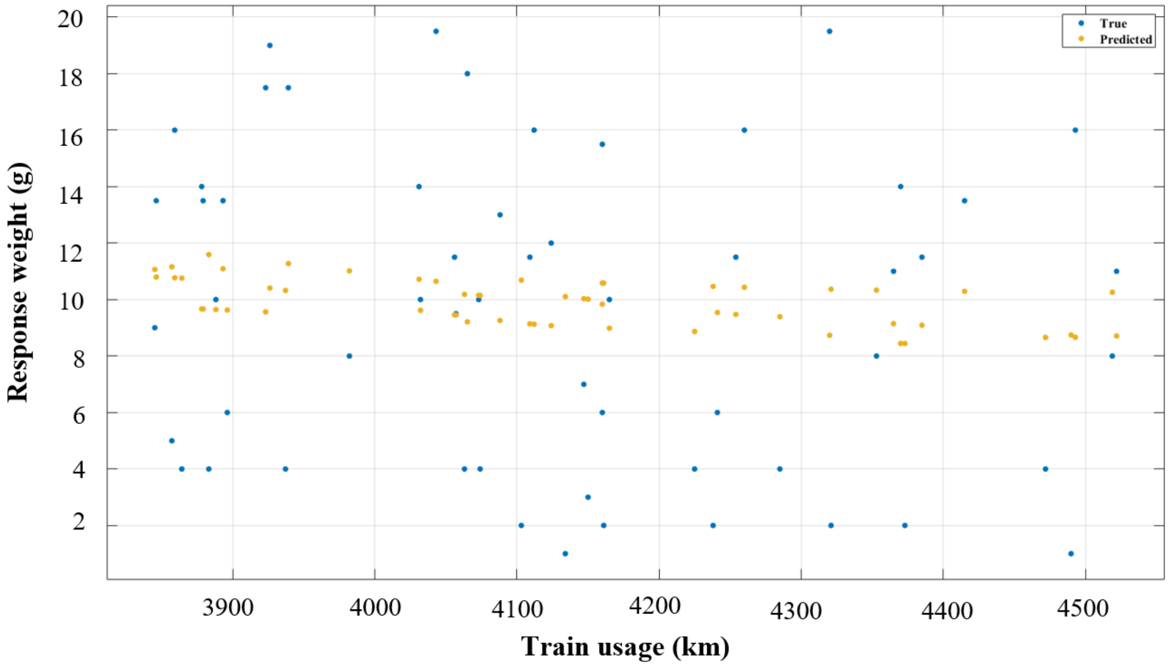

FIGURE 5. Flange lubricator SVR weight wear predictive model.

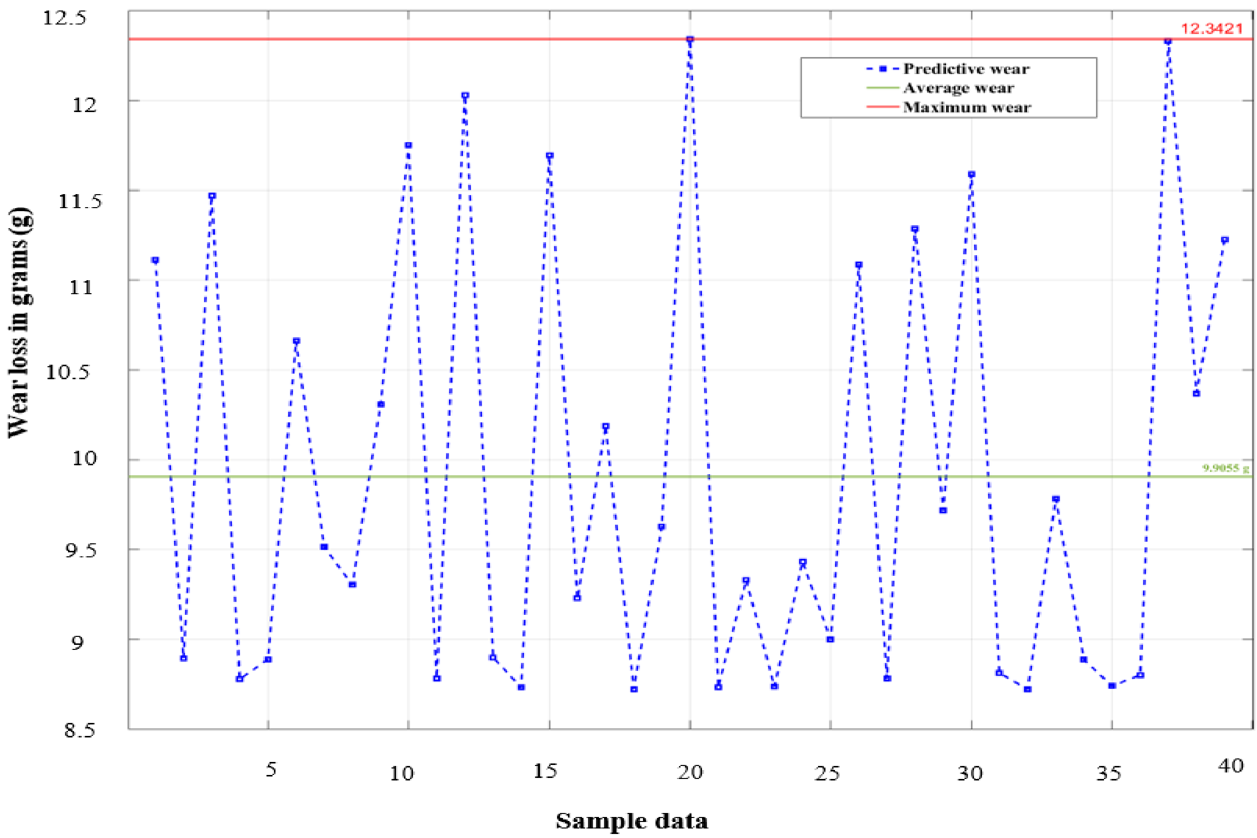

FIGURE 6. Predicted wear loss of flange lubricators using test data.

the worst-case scenario of flange lubricator wear rates. While the predicted values are primarily concentrated in the centre and provide sufficient room to accommodate additional flange lubricator wear loss, the maximum wear rate is instead considered to highlight the extreme worst-case scenario and pessimistic view of the wear loss to avoid compromising

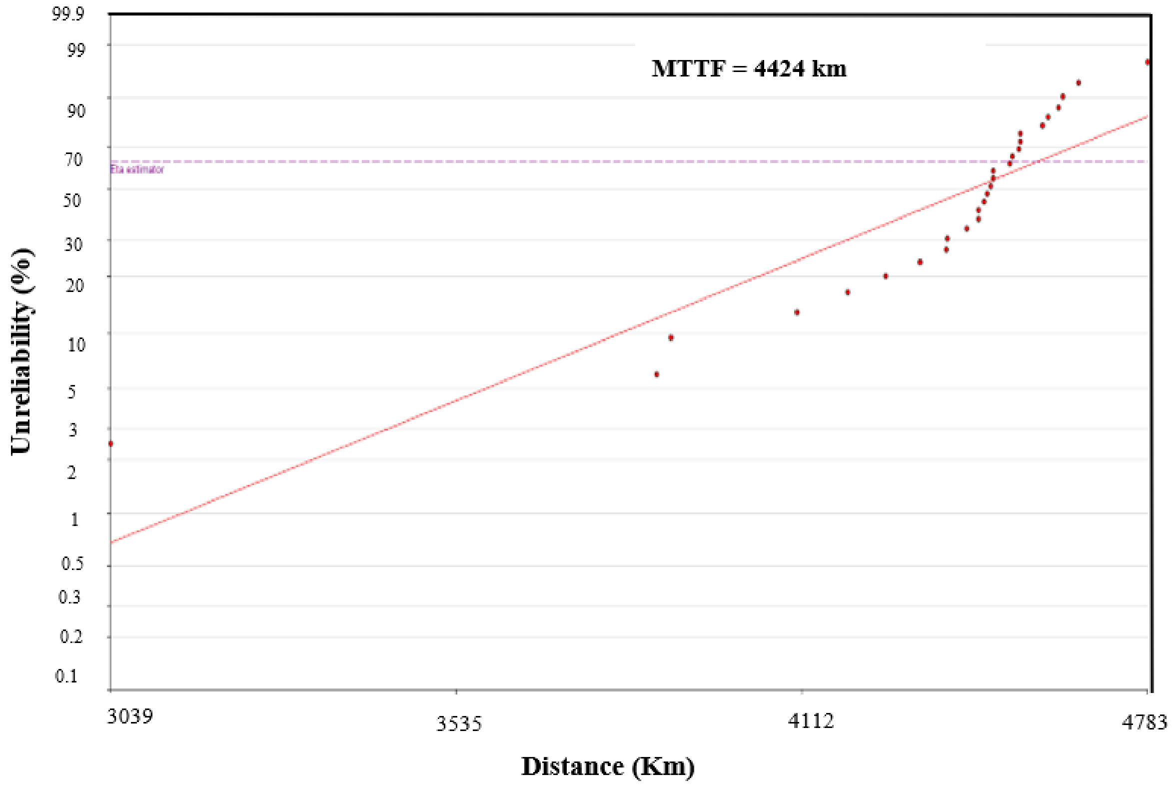

FIGURE 7. Flange lubricator failure rate for the failure threshold.

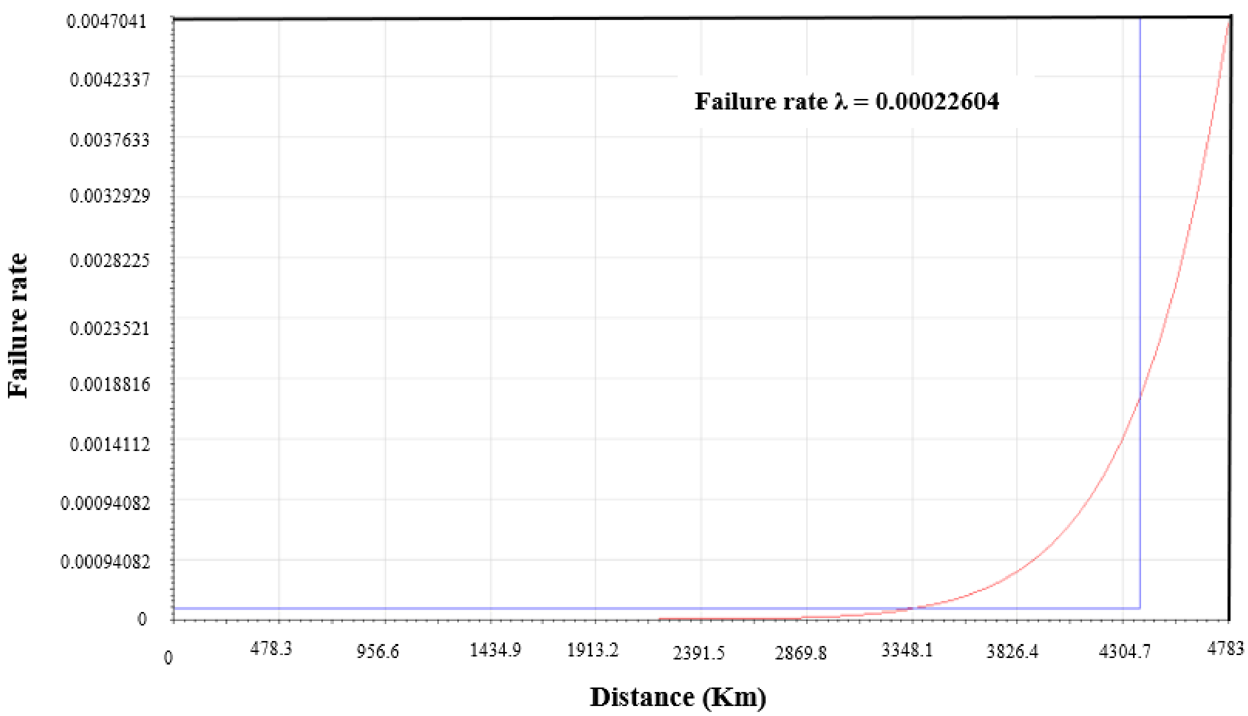

FIGURE 8. Flange lubricator cumulative probability plot for the failure threshold.

safety. Therefore, it provides assurance and confidence in the proposed maintenance intervals. The failure threshold was estimated to be 4424 km, as indicated by the failure rate and cumulative probability plots in Figures 7 and 8, respectively, by using the premature flange lubricator failure data in column 4 of Table 1. Thus, at least 50%, which is equivalent to

TABLE 2. Results of performance hyperparameters based on varying training data.

	Training data hyperparameters (σ, ε, C)		
	56 (4.000, 0.723, 7.230)	28 (4.000, 0.797, 0.797)	10 (4.000, 0.704, 7.040)
RMSE	5.4879	6.2392	6.1901
MAE	4.7856	5.3581	5.1708

TABLE 3. Predictive performance of SVR compared with other machine learning techniques.

ML	RMSE	MAE
SVR	5.4879	4.7856
GPR	5.6106	4.8606
MLR	5.4906	4.732

TABLE 4. Proposed risk-informed flange lubricator inspection interval.

Predicted wear (g)	12.3421
Failure threshold (km)	4424
Legal disposable limit (g)	5
Recommended risk-based inspection based on wear and threshold failure analysis	Every 4000 km

one flange lubricator, could have failed by the time the legal disposal limit of 5 g is reached. Despite that there are two flange lubricators per wheel housing (provisions for redundancy), in the case of risk-informed maintenance inspection intervals, the threshold tolerance cannot be exceeded. Given the estimated worst-case (maximum), estimated wear rates and threshold failure results, a risk-informed maintenance interval of 4000 train kilometres was proposed, as shown in Table 4. The proposed recommended risk-inspection interval of 4000 km offered protection and maintained the integrity of the flange lubricator, wheel, and railhead, including lessening the likelihood of excessive wheel wear that can ultimately lead to an accident. As a result, a 4000 km maintenance frequency provides an optimal balance between railway safety and flange lubricator cost-effectiveness. When new wear data and a failure threshold become available, the SVR with the threshold failure method can update the model parameters, including the failure threshold.

V. CONCLUSION

In this paper, a novel adaptive SVR with a failure threshold method was proposed for establishing an optimised inspection interval for maintenance of a railway composite flange lubricator with multiple failure mechanisms due to nonlinear and complex environmental factors. The proposed model integrates failure analysis of engineering materials and components as well as asset management techniques into a single framework. In contrast to other failure analysis methods, the proposed method uses the training data to establish hyperparameters for the SVR model and dynamically adjusts the hyperparameters for new input data and operational requirements. At the same time, the inclusion of a failure threshold enables cross-validation of the proposed interval options that were obtained from the SVR wear rate analysis to enable appropriate estimation of the RUL, which eventually informs risk-based maintenance inspection. The innovative method of using multivariate regression with predictive analysis for both random and systemic failures is demonstrated in our proposed model. The proposed model integrates machine learning regression for wear analysis with failure analysis technique.

The adaptability of the parameters of the SVR model, for dynamic training data, has superior prediction capabilities for a small data sample compared to other machine learning models. The results obtained in the case study demonstrated that while the SVR model was particularly precise in the estimation of wear rate, the proposed maintenance interventions based on the wear rates could only be a limiting factor in the assessment of risk and likely accident scenarios. However, the inclusion of the failure threshold provided a more robust analysis and perspective of underlying factors that enhanced a measured risk-informed maintenance inspection. In addition, the adaptive updating of the SVR and failure threshold method provides the unique capability for changes in component characteristics and evolution of ageing components due to multiple factors such as a varying operating context that should be adequately captured in future risk-informed maintenance decisions. Although, the scenarios considered in the current study indicate that the SVR predictive model shows superior performance with a small data sample, it would be useful to further validate this finding by considering other suitable machine learning techniques. With new input measurement data, the accuracy of predictions of the results from the proposed model can be improved over time. Hence, focusing on continued improvement in the input measurement data collection process is critical to obtain precise and accurate results.

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