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Reliability Analysis for Automobile Engines: Conditional Inference Trees

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Abstract

The reliability model with covariates for machinery parts has been extensively studied by the proportional hazards model (PHM) and its variants. However, it is not straightforward to provide business recommendations based on the results of the PHM. We use a novel method, namely the Conditional Inference Tree, to conduct the reliability analysis for the automobile engines data, provided by a UK fleet company. We find that the reliability of automobile engines is significantly related to the vehicle age, early failure, and repair history. Our tree-structured model can be easily interpreted, and tangible business recommendations are provided for the fleet management and maintenance.

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Keywords: Reliability Analysis; Conditional Inference Tree; Automobile Engines; Fleet Management; Maintenance

1. Introduction

During operation of a fleet, the condition of vehicles declines due to degradation and ageing, which may further cause failures. Maintenance is crucial in the fleet management in order to achieve the optimal availability of vehicles and also reduce the total cost, including maintenance cost and system cost due to idle time. Typically, the maintenance of vehicles in a fleet is scheduled based on a certain period of time or a certain number of miles, depending on which one comes earlier. In this work, we find that the reliability of automobile engines in fleet vehicles is not homogeneous and actually depends on other covariates.

Identifying the key covariates can support the fleet manager in making maintenance decisions. In the present body of literature, the reliability analysis with covariates for machinery parts has been extensively studied by the Proportional Hazards Model (PHM) [1-4] and its variants [5-8]. However, transforming the estimation results from the PHM into tangible business recommendations tends not to be straightforward.

The classification and regression tree model is introduced by Breiman et al. [9]. The results from tree-structured models can be interpreted in a straightforward way [10, 11]. However, an exhaustive search procedure for the tree model has two problems: overfitting and selection bias [9, 12, 13]. The Conditional Inference Tree, developed by Hothorn et al. [14], solved the two problems by applying the appropriate statistical test procedures to both variable selection and stopping criteria.

In this paper, a novel method, namely the Conditional Inference Tree [14], has been employed in order to conduct the reliability analysis on a sizable dataset of automobile engines. There are mainly two contributions from this study. Firstly, our tree-structured model can be easily interpreted, facilitating more constructive communications with practitioners. Secondly, unlike most machine-learning based models, which lack a theoretical foundation, the Conditional Inference Tree employed in this study is based on a well-defined theory of conditional inference procedures. To the best of our knowledge, this is the first study to use a Conditional Inference Tree for the reliability analysis on automobile engines.

Our main findings include: i) vehicle age is the most important covariate in determining the reliability of automobile

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engines; ii) early failure can largely deteriorate the reliability of automobile engines; and iii) engines with a large number of repair records in old vehicles have the least reliability. Based on the results of the Conditional Inference Tree, tangible business recommendations are provided for the fleet management and maintenance.

2. Literature Review

In the literature, the reliability models with covariates can be categorised into three groups: parametric, nonparametric models, and machine-learning based models.

Parametric models assume that the time-to-event (duration, lifetime, failure time) of a system follows a specific parametric distribution, such as exponential, Weibull, lognormal, and log-logistic. The accelerated failure time (AFT) models belong to the parametric category. The effect of a covariate in an AFT model is to act multiplicatively on the failure time or its transformations. The parametric models are only suitable for the cases in which the historical data follows the specified distribution. However, it is sometimes difficult to find a parametric distribution to fit the historical data in practice. If there is misspecification in the underlying distribution, the results from parametric models could be inaccurate. Newby [4] reported the impact of misspecification in the AFT models. Mettas [15] analysed the stress-type accelerated life data by the AFT models of the Weibull and lognormal distributions for different censoring schemes.

In the nonparametric models, the PHM, suggested by Cox [16], is one of the most extensively used tools by the reliability analysis due to its flexibility that regression coefficients can be estimated using partial likelihood without the specification of the baseline hazard function. The effect of the covariates is assumed to act multiplicatively on the hazard rate or its transformations. This property is referred to as the proportionality property, which is the basic assumption of the PHM. The proportionality property should be carefully checked when using the PHM. Kumar and Klefsjo [1] provided a review of the literature on the PHM. Kumar and Westberg [3] discussed the effect of operating conditions on the lifetime of a system in both the PHM and AFT. A discussion on choosing between the AFT and PHM is provided by Newby [4].

A number of variants and extensions of the PHM are proposed in order to address the cases in which the proportionality property is violated. Anderson and Senthilselvan [5] extended the PHM to allow for time-varying covariate coefficients, which is referred to as the two-step regression model. They proposed the conditional log-likelihood to estimate the regression coefficients. However, this model is likely to suffer a large number of breakpoints. The population can be divided into different strata according to a single covariate or a set of covariates. The Stratified PHM assumes that the hazard rate is proportional within the same stratum but not across different strata. Hence, the baseline hazard rate could be different for different strata. The coefficient in the Stratified PHM can be estimated by a similar likelihood method in Cox [16]. Kay [6] applied the Stratified PHM in the data from a clinical trial in medicine. Kumar [7] employed the Stratified PHM in the reliability analysis of repairable systems. One disadvantage of the Stratified PHM is that the estimated coefficients could be inaccurate in the case of a small sample size. The Extended Cox Regression Model extends the PHM to simultaneously analyse the effect of time-independent and time-dependent covariates [17]. One flaw of this model is that the functional form on the time-dependent covariates must be defined over time. Fisher and Lin [8] demonstrated how to select the correct form of a time-dependent covariate by four medial examples. Misspecification on the functional form could result in a great potential of bias [8]. Other variants of the PHM include: the Proportional Intensity Model [18], Proportional Odd Model [19], Proportional Covariate Model [20], etc. Gorjian et al. [21] provided a review of the literature on reliability models with covariates.

Due to the increase of computational power, a large number of machine-learning-based methods have been applied in the field of reliability analysis. Chatterjee and Bandopadhyay [22] developed a neural network-based model to forecast reliability. Their model has two main components: selecting the input variables by maximising the mean entropy value and selecting the neural network parameters by a genetic algorithm. The authors demonstrated that their model was accurate in forecasting the failure of a load-haul-dump machine. Tamilselvan and Wang [23] applied the deep belief network to the aircraft engine health diagnosis and electric power transformer health diagnosis. Their method is constructed through a hierarchical structure with multiple stacked restricted Boltzmann machines. This entails the advantages of fast inference and encoding complex network structures. Wei et al. [24] conducted the reliability forecasting by the support vector regression with dynamically updating parameters when a new observation comes. The dynamical updating mechanism is implemented via particle filtering. Their four application results showed that their dynamic-version support vector regression is more robust than the static-version one. Another study also based on support vector regression is conducted by Nieto et al. [25]. They utilised particle swarm optimisation with kernel parameter settings in the training procedure in order to improve the regression accuracy. The method is applied to the prediction of the remaining useful life of aircraft engines. The advantage is that their model does not need the previous operation stats of the engine. Dai et al. [26] proposed a multiwavelet linear programming support vector regression method for the reliability analysis. The idea of their method is to construct the autocorrelation function of multiwavelets into a kernel, which is used in linear programming support vector regression. They demonstrated that the method is more efficient than the classical support vector regression. Other machine-learning based methods applied in the field of reliability analysis include: adaptive wavelet frame neural networks [27], complex-valued neural networks [28], least square support vector machine [29], evidential reasoning algorithm [30], accelerated Monte Carlo with support vector machine/logistic regression [31], etc. Huang et al. [32]

provided a review of the current research status and future trends in the literature on support vector machine applied in the estimation of the remaining useful life.

However, most machine-learning based models suffer a lack of theoretical foundation and are usually regarded as a 'black box'. It is sometimes dangerous to solely rely on the output of those models to make operational decisions because of data-mining and over-fitting problems. In terms of the Conditional Inference Tree used in this study, Hothorn et al. [14] have shown that its recursive partitioning procedure is fully supported by a well-defined theory of the conditional inference procedure. The input variable selection and stopping criterion are based on formal hypothesis tests, mitigating the problems of over-fitting and selection bias in the exhaustive search algorithm in the tree-based models. In addition, although many machine-learning methods show good performance, the practitioners are still reluctant to employ them in the practical implementation of the reliability analysis because those methods are 'too complex to explain'. Our tree-structured model can be easily interpreted, facilitating more intuitive communications with practitioners.

Reliability analysis provides insights and implications for predictive maintenance and preventive maintenance. Zhou et al. [33] proposed a reliability-centred predictive maintenance policy that performs an imperfect preventive maintenance whenever the system reliability reaches the threshold. You et al. [34] employed the extended proportional hazards model to model the system reliability and further developed two component-level control-limit preventive maintenance policies. Xia et al. [35] assumed that the hazard rates are available and make the machine-level decision for availability-effective and cost-effective maintenance intervals.

3. Data

The Time Between Failure (TBF) of the automobile engine data was collected from a sizable fleet service provider in the United Kingdom. Our analyses focused on most recent relevant subset of TBF data with a total sample size = 1430. Each engine repair event can be triggered by a scheduled service or an unscheduled fault. We distinguish between scheduled and unscheduled records. The TBF in a scheduled event will be treated as a *right-censored record* since the theoretical TBF could be longer without the scheduled service. The TBF in an unscheduled fault will be treated as an *exact record*.

Table 1 shows the descriptive statistics of the TBF. There are 1,430 records of TBF. 911 out of the total records are due to unscheduled faults, and the remaining records are triggered by scheduled services, which are treated as right-censored data. The median is 476, with the confidence interval (440, 525) being estimated using Greenwood's method [36]. According to the quantile values, 10% of all records are shorter than 61 days, and 10% of all records are longer than 1,538 days.

Table 1 Descriptive Statistics

number of records	1430
number of events	911
10% quantile	61
30% quantile	236
Median	476
70% quantile	840
90% quantile	1538
median lower confidence limit	440
median upper confidence limit	525

4. Method

In tree-structured regression models, the exhaustive search procedures of the recursive binary partitioning are associated with two structural problems: overfitting and selection bias towards covariates with many possible splits or missing values. An unbiased recursive partitioning was designed by Hothorn et al. [14] in order to tackle the two problems. They developed the theory of conditional inference trees leading to the estimation of a regression relationship by binary recursive partitioning in a conditional inference framework. Interested readers can refer to the mathematical details in Ref. [14]. We briefly explain the procedure of the algorithm here.

> *Step 1)* Conduct a global test of independence between all covariates and the response variable. If the outcome is 'not reject', the procedure needs to be stopped. Otherwise, the procedure proceeds to find the covariate with the strongest dependence to the response variable.
>
> *Step 2)* Conduct a binary split in the selected covariate.
>
> Recursively repeat *Step 1)* and *Step 2)* until the global test of independence is not rejected.

In order to avoid the systematic tendency towards covariates with many possible splits, the key idea is the separation of variable selection in *Step 1)* and splitting procedure in *Step 2).* The stopping criterion is based on the global null hypothesis of independence between the response and any covariate, which is intuitive and statistically justified. It has been shown that the resulting trees by this algorithm have the predictive performance as good as that of established exhaustive search procedures but with lower computational costs [14].

As for our practical implementation, we choose the significance level at 5% for the independence test to determine the level of the covariates in the tree. Additionally, we set the minimal bucket in the terminal nodes at 50.

The next step is to identify the appropriate covariates, which may play a role in determining the TBF. We have identified the following potentially important covariates that may have a significant impact in determining the reliability of automobile engines.

- **Vehicle age (*VAge*):** the time difference (in years) between the repair date and the registration date of the vehicle.
- **Cumulative miles (*CumM*):** the distance (in 1000 miles) the vehicle has travelled from its registration date to the repair date.
- **Average miles (*AvgM*):** the distance per unit time (in 1000 miles/year) of the vehicle has travelled before the repair date (in 1000 miles/year). It is calculated by the cumulative miles divided by the vehicle age.
- **Job intensity (*JobInt*):** the distance per unit time (in 1000 miles/year) of the vehicle has travelled between the repair date and the next repair date. It is calculated by the miles travelled in the next TBF divided by the time length of the next TBF.
- **Number of repairs (*nRepair*):** the number of times the vehicle engine has been repaired in the garage before the repair date.

Other covariates (e.g. drivers' behaviour, operational information, geographical information, and environment information) can be considered. However, the record of that information is not available in our dataset.

5. Empirical Results

Figure 1 shows the results of the final tree-structured survival model for the automobile engine TBF data. The terminal nodes in the tree show the Kaplan-Meier estimates of the TBF (in days) of the partitioned groups. Interestingly, *AvgM* has been excluded from the tree models, implying that it is insignificant in affecting the survival function of automobile engines.

Table 2 presents the median and its confidence interval for different nodes in all three levels. We can find that the most important covariate is *VAge* because it is located in the root node. With the cutting-point at 8.025 years old, the difference in the median of Node 2 (median 616) and Node 9 (median 240) is substantial, 616-240=376 days. Hence, a more suitable preventive maintenance policy could be taken with the engine used in vehicles more than 8.025 years old. In other words, the scheduled services for checking the engine could be more frequent for relatively old vehicles.

Given the engine usage in vehicles less than 8.025 years old, the second important covariate is *nRepair*. If the engine has been faulty more than once, its TBF is significantly reduced, as can be shown by the difference between the median in Node 3 (median 709) and Node 6 (median 446) is 709-446=263 days. Thus, the early failure in the automobile engines will dramatically reduce the TBF. Avoiding the early failure is necessary in order to enhance the reliability of engines. For the vehicles with early failure in the engines, predictive maintenance could be more suitable.

Comparing Node 4 (median 823) and Node 5 (median 463), we can draw the conclusion that the usage, *CumM*, plays an important role when the vehicle is relatively new (less than 8.025 years old) and has no early failure. Compared to vehicles with more than 18.52K cumulative miles, vehicles with less than 18.52K cumulative miles have a higher survival function, with the difference in the median of 823-463=360 days. As can be observed in Figure 1, the survival function in Node 4 decreases slowly, while the survival function in Node 5 has a relatively steeper downward slope. In order to enhance the reliability of the engine, preventive maintenance with less interval of time could be considered in the case of relatively new vehicles which have travelled more than 18.52K.

Table 2 Kaplan-Meier estimates of different nodes

	n	events	median	95% LCL	95% UCL
First level					
Node 2	1148	698	*616*	545	686
Node 9	282	213	*240*	203	261
Second level					
Node 3	732	419	*709*	631	770
Node 6	416	279	*446*	361	525
Third level					
Node 4	465	256	*823*	745	896
Node 5	267	163	*463*	370	596
Node 7	236	145	*701*	616	771
Node 8	180	134	*256*	164	341
Node 10	231	175	*261*	243	290
Node 11	51	38	*74*	55	101

When the vehicle has an early failure in the engine, the *JobInt* becomes critical in determining its survival function. The difference between the median in Node 7 (median 701) and 8 (median 256) is significant, i.e. 701-256=445 days. Hence, it is sensible to assign relatively less intensive jobs to vehicles with early failures. Otherwise, the engine could have the next failure in a relatively short period of time.

Comparing Node 10 (median 261) and Node 11 (median 74), the difference between the median of the TBF is large, 261-74=187 days. The survival function of Node 11 in Figure 1 fades to zero in a fast manner. Depending on the repair cost, the fleet manager could consider scrapping the engine used in this group of vehicles, which are more than 8.025 years and have been repaired more than six times. An alternative option is to remanufacture the engine.

6. Conclusion

A novel method, namely the Conditional Inference Tree, has been applied to the reliability analysis of automobile engines. Compared with the PHM and its variants, our tree-structured model has a straightforward interpretation, which can be transformed into tangible business recommendations for the fleet manager. Compared with other machine-learning based methods, the Conditional Inference Tree is based on the well-defined theory of conditional inference procedures.

Based on the estimated tree structure, tangible business recommendations are provided for the fleet management. It has been revealed that the most important covariate is the vehicle age, with relatively important covariate being the number of repairs, the cumulative miles of the vehicle, and the job intensity. Avoiding early failure is necessary to enhance the reliability of engines. Extra care should be taken with engines in relatively new vehicles which have travelled more than 18.52K miles. It is sensible to assign relatively less intensive jobs to the vehicle with early failures. Fleet managers could consider scrapping or remanufacturing the engine if it has been repaired more than 5 times and it is being used in vehicles more than 8.025 years old.

The limitation of our model is that the tree-structure might be unstable in different time periods. In other words, the estimated tree structure from the historical data might not be appropriate for future data. Hence, it is necessary to monitor the tree-structure with new coming observations in practice.

Further research studies wish to explore the forecasting ability of the Conditional Tree Model, with the comparison to the PHM and its variants. It could also be potentially beneficial to use bootstrap aggregating (a.k.a. bagging) and random forecasts to improve the forecasting accuracy of the Conditional Tree Model.

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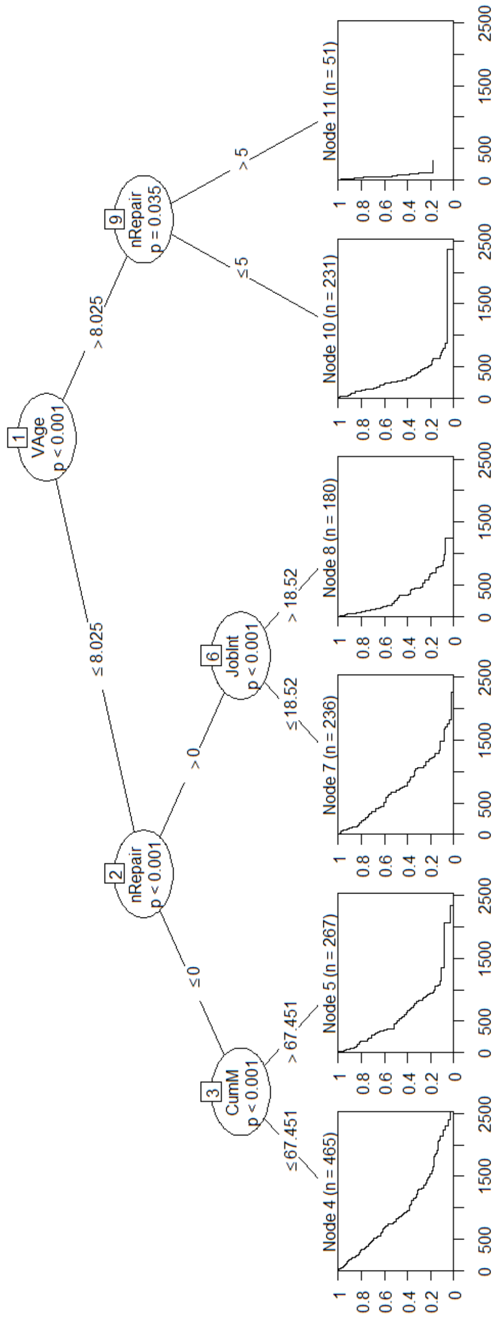

Figure 1 Tree-structured survival model for the automobile engine data. The terminal nodes in the tree show the Kaplan-Meier estimates of the Time Between Failure (in days shown in the x-axis) of the partitioned groups.

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