A Reliability Study of Railway Switch and Crossing Components

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Abstract

Within any railway network Switches and Crossings (S&C) are essential. They allow trains to change tracks, allowing different routes to be selected. Despite their necessity, they generally have a lower reliability than plain line track and are often subject to breakdowns due to the high number of interlinking electrical and mechanical components they contain. Due to their location such as station throats and major junctions, S&C breakdown is generally very disruptive to traffic causing significant delays. Ensuring that S&C units are maintained correctly and minimising their risk of failure, is therefore of critical importance to railway asset managers. This research uses maintenance and failure data to determine probability distributions for the degradation, failure, inspection and maintenance of nine critical components within S&C units. These distributions can then be used within an asset management framework to simulate the expected operational behaviour of an S&C unit under a given set of conditions, allowing more informed asset management decisions to be taken.

Keywords

Railways, Switches and Crossings (S&C), Asset Management, Poisson Process, Weibull Process.

Introduction

Railway infrastructure is key to the prosperity and success of countries and economies worldwide. Moreover, rail services must be reliable and punctual in order to attract both passenger and freight customers[1,2]. Having reliable infrastructure is critical to this; it is the responsibility of railway infrastructure asset managers to ensure the infrastructure is maintained effectively in order to meet safety and performance targets whilst adhering to financial constraints, to satisfy both customers and stakeholders. This research focuses on the asset management of one aspect of the railway infrastructure; Switches and Crossings (S&C).

S&C are essential to the railway network and allow trains to switch between and cross over other tracks[3]. Despite their necessity, S&C generally have a lower reliability than plain line track and are responsible for a significant number of delays, with Network Rail reporting that points failures caused 481,719 delay minutes to passenger and freight services on the British railway network in 2019/20[4]. Deutsche Bahn reported that 19% of delay minutes on the German railway were caused by S&C failure in 2010[5].

This paper presents a reliability study of the key components within S&C units, determining probability distributions to model their degradation, failure, inspection and maintenance. These distributions can subsequently be used to populate an asset management framework such as that presented in the companion paper[6]. The outputs of asset management frameworks can then be used to assess how asset management decisions will impact Key Performance Indicators (KPIs), such as punctuality, and life cycle cost, allowing more informed decision making.

There are many different types of S&C unit including turnout, scissor crossing and Fixed Diamond (FD) crossing. Their specific layout can be adjusted to meet the capacity and capability requirements of the network, as well as geographical constraints. They are made up of various electrical and mechanical components, and not all components are present in all designs, the nine most common components are:

(i) Ballast

(ii) Bearer

(iii) Check and Wing Rail

(iv) Crossing

(v) Fastening

(vi) Slide Chair

(vii) Stretcher Bar

(viii) Stock Rail

(ix) Switch Rail

These components are illustrated in Figure 1 which shows a schematic of a turnout S&C. The ballast is the select crushed granular material placed as the top layer of the substructure in which the sleepers are embedded[7]. It is composed of medium to coarse gravel-sized aggregates typically (20-50mm). The optimum thickness is 250-300mm[8]. There are three main types of rail in an S&C unit: the stock rails which are fixed, the switch rails which move allowing the train to change track; and check and wing rails used to guide the train wheels and ensure the train stays on the correct track as it passes over the switch. There is a gap in the stock rail, to allow the train wheels to cross over the other

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track, this is known as the crossing. The crossing experiences very high impact forces[9,10] and deteriorates significantly faster than most other S&C components.

Stretcher bars are used to join the two switch rails together and ensure the gauge is maintained. They are safety critical and stretcher bar failure has led to catastrophic derailments in the past, such as that at Potters Bar (UK) in 2002[11].

Bearers are the special name given to sleepers used within an S&C unit. The bearers are typically spaced around every 0.6 metres[12] and are normally longer than a standard sleeper. Bearers can be made of either wood or concrete. In the UK timber is widely used in S&C design as it is simple to shape and straightforward to attach fastenings to. As of 2017 around 70% of turnout switches in the UK were built on timber bearers. However, for high-speed design timber can often not provide the necessary support and therefore concrete bearers are used much more widely for high speed turnouts[3]. The bearers are embedded in the ballast and ensure that the rails are maintained at the correct alignment and gauge. Fastenings or clips are used to attach the stock rails to the bearers. A great variety of fastening systems exist, new types are regularly added, in order to keep up with changes in requirements or due to the availability of new materials[8].

As the switch rails move, they cannot be fixed with rigid clips, slide chairs are used instead as they allow the rails to move in the horizontal direction. The switch rails are moved using Point Operating Equipment (POE). The POE can be electric, hydraulic or pneumatic[13]. As the POE is an electrical component its failures were not recorded in the datasets analysed in this research. Subsequently, the POE is not considered in the remainder of this paper.

This paper presents a reliability study of the key components listed above; determining probability distributions to model their degradation, failure inspection and maintenance.

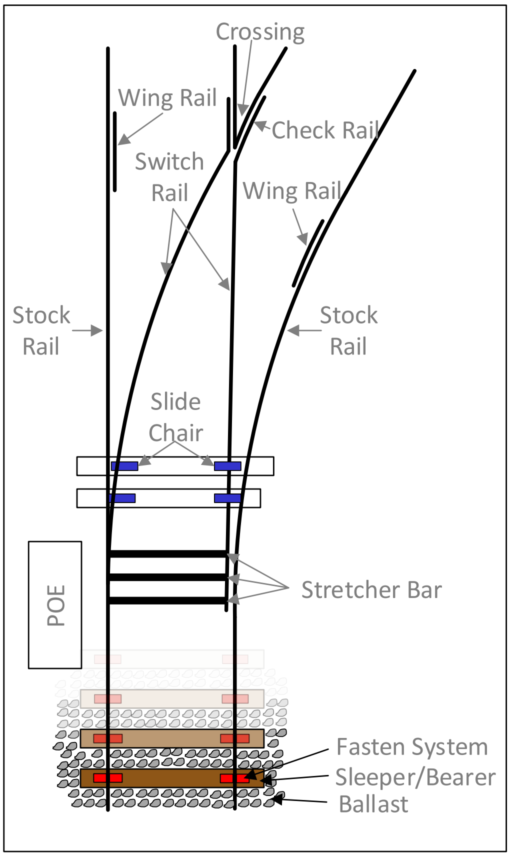

Figure 1. Turnout layout with key components.

There are a number of processes that drive a component's reliability and maintainability and its subsequent availability. These are:

(i) Degradation

(ii) Failure

(iii) Inspection

(iv) Maintenance

These processes are outlined in the diagram in Figure 2.

When managing an S&C one of the fundamental questions an asset manager will need to answer, in order to make good asset management decisions, is the proportion of the time the planned timetable cannot operate because the S&C is not performing as required. To predict the component availability a forecast for the four processes outlined in Figure 2 is required. This paper builds on the work presented by Rama and Andrews[13] by considering maintenance records in parallel with failure records, allowing deterioration and failure to be modelled. The paper also introduces a methodology to model the time between inspections and the time to complete maintenance activities.

The S&C unit will experience multiple failures and repairs throughout its life which will impact its availability. However, it is impossible to say with certainty when these events will occur; even under seemingly identical conditions the timing of these events will vary, therefore it will never

Reliability Analysis

Reliability is the study of a component's ability to perform as required; reliability analysis is used throughout engineering. One of the most widely accepted definitions of reliability is 'the probability of a device performing its purpose adequately for the period of time intended under the operating conditions encountered'[14].

Closely linked to reliability is maintainability, which provides an assessment of how quickly a device can be returned to its operational state following failure.

Reliability and maintainability can be linked through the concept of availability which is defined as 'the fraction of the total time that a component or system is able to perform its required function'[15]. Availability provides a combined view of how often a component or system fails and how quickly it can be repaired following failure. Availability can be expressed as:

$$A = \frac{MTTF}{MTTF + MTTR} \quad (1)$$

Where MTTF is the mean time to failure (measure of reliability) and MTTR is the mean time to repair (measure of maintainability).

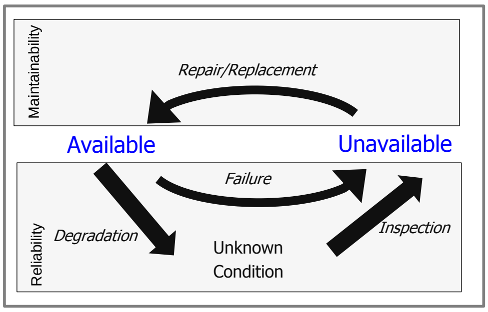

Figure 2. Component life cycle.

be possible to say categorically whether the S&C will be available at a given time.

Handling events whose occurrence is non-deterministic is a problem commonly experienced in many branches of engineering and the branch of statistics used to overcome these difficulties is probability theory [15]. Probability theory expresses the probability (between 1 and 0) of different events occurring based on some known distribution. This allows inferences to be made about the true characteristics of the system, allowing numerical quantification of the likelihood of different scenarios, and identification of the most likely (and unlikely) scenarios.

Probability Distributions

A vast range of different probability distributions exist, which can be used to model the likelihood of different events occurring. These are generally grouped into two types:

(i) Continuous

(ii) Discrete

Continuous distributions can take any value, whereas discrete distributions are limited to certain values (for example integers). Due to the diverse range of components within an S&C unit, both continuous and discrete distributions have their uses. For components where the exact time between repairs is known, continuous distributions are most useful. However, for other components, where the data collected does not identify the specific component that was repaired, it can be easier to model the number of repairs expected in a given period of time, making discrete distributions more appropriate.

Continuous Probability Distributions

When modelling reliability using a continuous probability distribution, it is common practise to explore a range of different continuous probability distributions and then select the most appropriate model (if any) using a 'goodness of fit test'.

There are a range of techniques to fit continuous probability distributions to reliability data. These include the method of moments [16], regression methods, [17] and maximum likelihood methods [18].

There is no exact rule on when which method is the most appropriate. Nonetheless, as the data sets in this study were large and generally contained a significant amount of right censored data, the maximum likelihood method is chosen. The likelihood function for right censored data is given by:

$$L(\theta; x, \delta) = \prod_{i=1}^{N} [f(x_i; \boldsymbol{\theta})]^{\delta_i} [S(x_i; \boldsymbol{\theta})]^{\delta_{i-1}}, \quad (2)$$

where *f(t)* is the distribution Probability Density Function (PDF), totally determined by the parameter vector $\boldsymbol{\theta}$, $S(t) = 1 - F(t)$ is the survival function, and δ_i is the death indicator, taking the value one if unit *i* fails (requires repair) and the value zero otherwise. With *F(t)* being the Cumulative Density Function (CDF).

Within this study four of the most commonly occurring continuous probability distributions in engineering were tested for each data set. The distributions considered are:

(i) Exponential

(ii) Weibull

(iii) Normal

(iv) Log normal

Exponential distributions are denoted $E(\lambda)$, where λ is the failure or repair rate. Weibull distributions are denoted $W(\alpha, \beta)$, where α is the shape parameter, such that $0 < \alpha < 1$ indicates a decreasing failure rate, $\alpha = 1$ the distribution is equal to an exponential distribution and has constant failure rate, $\alpha > 1$ indicates an increasing failure rate. β is the scale parameter and indicates the characteristic life. Normal distributions are denoted $N(\mu, \sigma^2)$, where μ is the mean and σ^2 is the variance. Finally, log normal distributions are denoted $L(\mu, \sigma^2)$ where $e^{\mu + \frac{\sigma^2}{2}}$ is equal to the mean and σ^2 is the variance.

Once each of these distributions was fitted to the data, a goodness of fit test was used to assess which (if any) was the best fit to the data. There are a range of goodness of fit tests that can be used to evaluate how well a given sample data set fits a given distribution. Some of the most common goodness of fit tests include chi-square, Kolmogorov-Smirnov and Anderson-Darling [19].

In this study Weibull++ [20] is used for all distribution fitting. Weibull++ fits the data using the maximum likelihood method outlined in Equation (2) and assesses the goodness of fit based on three measures:

(i) $AVGOF$, from Kolmogorov-Smirnov method

(ii) $AVPLOT$, from the correlation coefficient

(iii) KV, from the likelihood value

Discrete Probability Distributions

For certain components it was not possible to identify exactly which component had failed and therefore it was more appropriate to model the number of failures expected in a given period of time, rather than trying to model specific component behaviour. Discrete probability distributions can be useful in this regard, one of the most widely used discrete probability distributions is the Poisson distribution:

Poisson Distribution The Poisson distribution[21,22] assumes that failures are independent, and the probability of failure is constant throughout time. The process is memoryless and the time of previous failures has no effect on the time of future failures. The probability mass function for the Poisson distribution contains a single parameter, λ, and is expressed using the following formula:

$$P(k) = \frac{\lambda^k e^{-\lambda}}{k!} \quad (3)$$

The time between failures thought to follow a Poisson distribution, can be modelled using the continuous exponential distribution.

Non-Homogenous Poisson Process One of the limitations of using the Poisson distribution as described in Equation (3) is that it assumes a constant failure rate. However, for some components in the S&C a constant failure or repair rate would not make sense. For example a repair might improve the condition but not return it to the new condition. Therefore, an increasing failure rate would be observed for this component.

To model this phenomenon the Non-Homogenous Poisson Process (NHPP) can be used; it assumes the rate of occurrence, u, is a function of time.

The NHPP can contain as many parameters as required to completely relate time to the rate of occurrence. A common two parameter function to relate the occurrence rate with time is:

$$u(t) = abt^{a-1}, \quad (4)$$

where a and b are positive constants. This choice was proposed by Crow[23] and is known as the Power Law NHPP or Power Law Process and has extensive applications in the study of repairable systems[24,25].

S&C Life Cycle Modelling

This section explores how real world S&C reliability and maintainability data, collected in the UK by Network Rail, can be used to determined distributions for the key processes in the component life cycle outlined in Figure 2.

There are many different types of S&C design, each containing components with differing properties and unique reliability characteristics. In the UK, Network Rail categorises turnout S&C units from size A (being the smallest with the tightest turnout radius) to size H[1] (being the largest with the shallowest turnout radius). A breakdown of the switch types on the UK network is given in Table 1. It can be seen that turnout size C is the largest cohort, this is often viewed as the baseline by Network Rail.

In an attempt to enhance the quality of outputs, it was decided to group together S&C with similar characteristics. The initial grouping was based on switch size. This approach groups switches with similar properties such as size, crossing angle and turnout radius. However, other factors such as rail weight, loading and number of operations may also influence the S&C behaviour. At the time of writing it was extremely difficult to align datasets containing traffic information such as tonnage and number of operations to the failure data, with the former significantly lacking in data. Therefore, these factors are not explicitly considered in this study. As future work the authors would like to explore how emerging techniques may allow these factors to be considered.

For the purpose of the analysis in this study the components were split into two groups:

(i) **Single (or low) occurrence components:** For the single occurrence components, it is possible to link failure and repair records to the specific component and hence a detailed history of the component's life can be created, therefore continuous probability distributions are most appropriate to model their behaviour.

(ii) **Multiple (or high) occurrence components:** For multiple occurrence components, records are generally insufficiently detailed to determine the exact component that was replaced. And therefore discrete probability distributions can be used to estimate the expected number of repairs in a given time period.

The complete list of single and multiple occurring components is given in Table 1 alongside the assumed number of components by switch type.

Table 1. Total amount of different switch types in the UK alongside the assumed number of components by switch type

Switch Type		A	B	C	D	E	F	G	FD
Number of units		257	2870	8177	2675	2115	719	405	540
Component	M/S								
Ballast	S	1	1	1	1	1	1	1	1
Check rail	S	1	1	1	1	1	1	1	1
Crossing	S	1	1	1	1	1	1	1	4
Fastening	M	60	70	80	100	120	140	150	110
Bearer	M	25	30	35	45	50	60	70	55
Slide chair	M	40	50	60	72	84	92	108	0
Stretcher bar	M	2	2	3	4	4	5	6	0
Stock rail	S	1	1	1	1	1	1	1	1
Switch rail	S	1	1	1	1	1	1	1	0

Component Degradation

For the key S&C components listed in Table 1, condition data is generally only available for ballast, the ballast is discussed separately at the end of the section. For the remaining components, in the absence of condition data, the degradation is estimated using maintenance records. A different approach is taken to model multiple occurrence components compared to single occurrence components due to differences in the data availability, the methodology used for each is outlined below:

Multiple occurrence components For multiple occurrence components, the data is usually not granular enough to distinguish between individual components. Therefore, the deterioration must be estimated solely based on the total number of repairs; the total number of repairs is denoted N and was determined using records in Ellipse, Network Rail's asset management system. In all cases it is assumed that components were repaired because they were degraded in some way.

As highlighted in the previous section, the Poisson distribution can provide a good approximation for the expected number of occurrences of an event in a given period of time when only the total number of occurrences in that period of time is known. Therefore, the Poisson process is considered suitable to approximate the expected number of replacements for multiple occurring S&C components in a given period of time. This approximation assumes that the replacement rate is constant.

Maintenance data was used to determine a Poisson distribution to model the number of replacements for the four multiple occurring components; the analysis was divided by switch type to allow a separate Poisson distribution to be determined for each switch size. The λ parameter for the Poisson distribution was determined using the following steps:

(i) **Determine the number of repairs**, aggregated by switch type.

(ii) **Adjust the number of repairs to account for unassigned records.** A number of replacement records had missing data and could not be assigned to a specific switch size, the number of unassigned replacement records is denoted U. To account for these unassigned records, it was assumed that they were distributed across the different switch types in proportion with the number of assigned records.

(iii) **Determine the mean number of replacements per year, λ.** This is calculated by dividing the total number of replacements by six, as data was collected over six years and further dividing by the number of switches of the given size. λ then describes a Poisson distribution for the expected number of replacements in a given year for a given switch type, for example for a size A switch we would expect 1.25 bearer replacements in a 50 year period.

(iv) **Determine the component replacement rate**. This was achieved by dividing the adjusted number of replacements by the length of the observation period in days, to determine the mean time between interventions. This value is then divided by the number of switches and the number of components as listed in Table 1.

The full breakdown of the number of repairs by component and switch size and the mean number of repairs per year is provided in Table 2 alongside the component replacement rate. A plot of each of the Poisson distributions based on the λ values given in Table 2 is provided in Figure 3. It can be observed that the fastenings and stretcher bars are expected to require the highest number of maintenance interventions. It can further be observed that generally the larger switches (Size G) required more component replacements than the smaller ones (Size A). There is a particularly strong correlation for the fastenings and stretcher bars. The most straightforward explanation for this observation is larger designs have more of these components, so there are more to fail. However, component failures are also thought to occur more frequently on the larger designs, as they are generally more heavily trafficked and have greater line speed and are therefore subject to higher impact forces.

Single occurrence components For the stock rail, switch rail, crossing and check and wing rail, as there is just a single component, it is possible to assign maintenance records

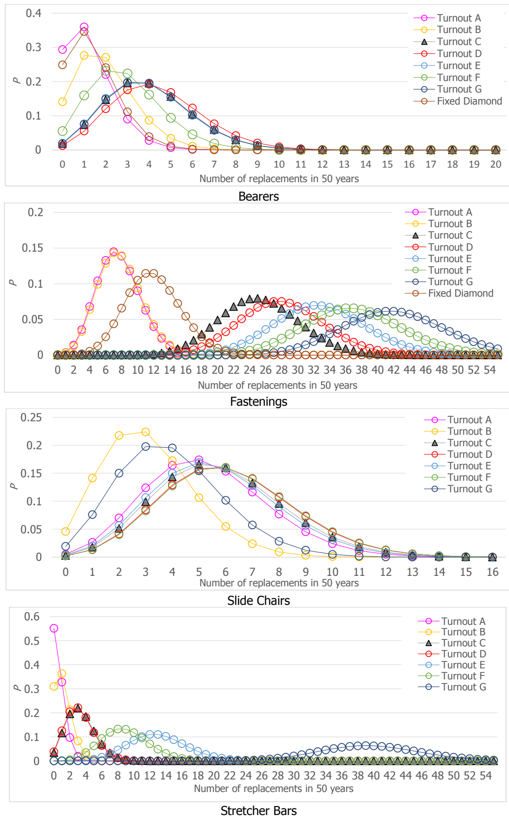

Figure 3. Poisson distribution for the number of component replacements by switch type.

to the specific component and from this the time between interventions of specific components (component lifetime) can be calculated.

Based on the maintenance records it is possible to identify complete and right censored lifetimes for each component. Nonetheless, the observation period was relatively short in comparison to the average complete lifetime, therefore the majority of the data was right censored. Right censored data occurs when full lifetimes are not observed as the component remains functioning beyond the end of the observation period. Censored data is still advantageous, as it is known that the actual component lifetime was at least this long.

Based on the maintenance records, the distribution of time between interventions was calculated in the following way:

(i) Use the switch ID to assign maintenance records to individual switches,

(ii) Determine complete lifetimes based on the time between interventions,

(iii) Determine censored lifetimes based on the time between the final observation and the end of the observation period and between the start of the observation period and the first intervention,

(iv) Use the maximum likelihood function in Equation (2) to fit the four distributions outlined to the lifetime data to determine continuous probability distributions to model the time between interventions,

Table 2. Multiple occurrence component replacements in 2191 days, replacement rate at cohort level, component level and adjusted component rate.

Component	Switch type	Known replacements	Adjusted number of replacements	Mean number of replacements per year, λ	Component replacement rate, (Day^{-1})
Bearer	Unknown	4968	-	-	-
	A	13	38	0.025	2.69$*10^{-6}$
	B	232	675	0.039	3.58$*10^{-6}$
	C	1349	3923	0.080	6.26$*10^{-6}$
	D	483	1404	0.088	5.99$*10^{-6}$
	E	344	1000	0.079	4.32$*10^{-6}$
	F	86	250	0.058	2.65$*10^{-6}$
	G	66	192	0.080	3.11$*10^{-6}$
	FD	31	90	0.028	1.39$*10^{-6}$
Fastening	Unknown	35705	-	-	-
	A	71	236	0.153	6.98$*10^{-6}$
	B	807	2681	0.156	6.09$*10^{-6}$
	C	7466	24805	0.506	1.73$*10^{-5}$
	D	2713	9014	0.562	1.54$*10^{-5}$
	E	2512	8346	0.658	1.50$*10^{-5}$
	F	960	3190	0.739	1.45$*10^{-5}$
	G	611	2030	0.842	1.54$*10^{-5}$
	FD	234	777	0.240	5.97$*10^{-6}$
Slide Chair	Unknown	10207	-	-	-
	A	12	163	0.106	7.25 $*10^{-6}$
	B	78	1062	0.062	3.38$*10^{-6}$
	C	417	5678	0.116	5.28$*10^{-6}$
	D	144	1961	0.122	4.65$*10^{-6}$
	E	105	1430	0.113	3.67$*10^{-6}$
	F	39	531	0.123	3.51$*10^{-6}$
	G	14	191	0.079	2.00$*10^{-6}$
	FD	n/a	n/a	n/a	n/a
Stretcher Bar	Unknown	10163	-	-	-
	A	1	18	0.012	1.63$*10^{-5}$
	B	22	404	0.023	3.21$*10^{-5}$
	C	180	3302	0.067	6.14$*10^{-5}$
	D	57	1046	0.065	4.46$*10^{-5}$
	E	180	3302	0.260	1.78$*10^{-4}$
	F	42	770	0.179	9.78$*10^{-5}$
	G	104	1908	0.791	3.61$*10^{-4}$
	FD	n/a	n/a	n/a	n/a

(v) Apply goodness of fit tests to determine which distribution is the most appropriate.

The ReliaSoft-Weibull++ package[20] was used to fit distributions to the component lifetime data using the maximum likelihood approach, using Equation (2). The number of complete and censored lifetimes alongside the best fitting distribution for the three components and eight switch types are detailed in Table 3. The check and wing rails had considerably fewer maintenance records than the other components, as such dividing them into eight cohorts based on the switch type led to very few records in each cohort. Therefore, several switch sizes were grouped to increase the number of records in each cohort. Turnout sizes A and B were combined as were sizes E, F and G.

Ballast and track geometry As aforementioned, the ballast's main role is to support the sleepers and maintain the track alignment. There are a range of different ways to assess the ballast condition, one of the most common being a ballast fouling index[26,27]. However, ballast maintenance decisions are usually governed by the track geometry, rather than the ballast condition itself. The track geometry is assessed using a number of measurements including: twist, vertical profile, horizontal alignment and gauge[28]. When modelling the track geometry it is common practice to discretise these continuous measurements into a number of discrete condition states and model the time to transition between them[29–31].

In the UK, Network Rail assesses the track geometry as being in one of five quality bands based on the horizontal alignment, vertical alignment and line speed. These categories are 'Good', 'Satisfactory', 'Poor', 'Very Poor' and 'Super Red'[2].

During a geometry inspection the geometry of the S&C will be measured and placed in one of the five quality bands outlined. By comparing the alignment at subsequent inspections it is possible to estimate the time taken to traverse the various different condition states. Nonetheless, the full maintenance history of the S&C would also be required as

Table 3. Distribution of time between maintenance interventions based on complete and censored lifetimes.

Component	Switch type	Complete lifetimes	Censored lifetimes	Degradation distribution (days)
Check & Wing Rail				
	A,B	4	80	W(0.60, 149000)
	C,D	17	526	W(0.63, 23637)
	E,F,G	5	126	W(0.50, 50000)
	FD	1	11	W(3.53, 2632)
Crossing				
	A	64	25	W(1.27, 20204)
	B	671	352	W(1.72, 1770)
	C	2395	5765	W(1.55, 1862)
	D	1001	2548	W(1.57, 1867)
	E	862	2506	W(1.51, 1994)
	F	322	1450	W(1.36, 2235)
	G	192	726	W(1.14, 2849)
	FD	241	135	W(0.36,3072)
Stock / Switch Rail				
	A	20	76	W(0.502,14392)
	B	466	896	W(0.554, 4792)
	C	3077	5511	W(0.562, 4232)
	D	1337	2140	W(0.565, 3556)
	E	962	2724	L(7.954, 8.343)
	F	396	599	L(7.530, 6.942)
	G	333	376	W(0.542, 2262)
	FD	106	352	W(0.561,10730)

the degradation of the ballast has been shown to be dependent on the maintenance history[29]. Aligning the maintenance and renewal records with the geometry data to determine a maintenance history for each S&C is beyond the scope of this paper, as such Weibull distributions were estimated based on engineering judgement.

The β parameters were estimated based on Subject Matter Expert (SME) suggestions of the time between geometry interventions (tamping or stoneblowing) at S&C units. These values were then compared to plain line values presented by Audley and Andrews[29] and found to be smaller; this was thought to be acceptable as the alignment at S&C is thought to deteriorate more quickly than on plain line track[32]. The SME suggested that alignment deterioration accelerated with age and therefore α parameters greater than unity were selected. This corresponds to the observation of Audley and Andrews[29], where α parameters were generally greater than one. The full list of distributions assumed is shown in Table 4.

Safety limit exceeding defects

The analysis so far has used maintenance records captured in Network Rail's Ellipse database to estimate the component reliability based on the time between interventions. However, many of the S&C components also have safety thresholds; if defects are found to exceed these thresholds action will be taken immediately; either an emergency speed restriction (ESR) or a line closure. These events are captured in the FMS (Fault Management System) database. Defects requiring an ESR or line closure were observed for the single occurrence components namely: stock rail, switch rail, check rail and crossing.

The FMS data was analysed to determine the expected number of failures, for the four components listed above for the eight switch types. Specific switches could be identified from the data, hence the time between failures of specific components could be determined. However the lifetimes were concluded not to be comparable, as the components would have undergone different maintenance cycles during each lifetime. As such a complete maintenance history of the component would be required in order to identify similar lifetimes. This level of analysis was beyond the scope of this paper.

As such a Poisson distribution was used to estimate the expected number of failures in a given period of operation. The methodology applied was similar to that used for the repair of multiple occurring components, outlined earlier in the paper. The total number of times the safety limit was exceeded was determined, this value was then adjusted to take account of unassigned records, finally this value was divided by the observation length and the number of switches of the given size to determine the mean number of failures per year. The observation length was slightly different for the different components, the maximum duration was $L = 4747$ days, with data collected between 2005 and 2017. The full list of λ values determined for each of the components and switch sizes is given in Table 5. Figure 4 shows an overall comparison of the expected number of failures in 50 years based on the values in Table 5. It can be observed that the switch rail is the most failure prone component, however there is little correlation between the switch types, with the switch size seemingly having little impact on the number of failures expected. It can be observed that crossing failures are significantly more likely on FD crossings, this is to be expected as there are four crossings in a FD crossing but only one in turnout designs.

Table 4. Ballast deterioration distributions.

Type	Transition	Number of passed interventions (Tamps and Stoneblows)						
		0	1	2	3	4	5	>5
Size A	Good → Satisfactory	W(1.80,825)	W(1.85,785)	W(1.90,745)	W(1.95,705)	W(2.00,665)	W(2.05,625)	W(2.10,585)
	Satisfactory → Poor	W(1.80,798)	W(1.85,758)	W(1.90,718)	W(1.95,678)	W(2.00,638)	W(2.05,598)	W(2.10,558)
	Poor → Very Poor	W(1.75,770)	W(1.80,730)	W(1.85,690)	W(1.90,650)	W(1.95,610)	W(2.00,570)	W(2.05,530)
Size B	Good → Satisfactory	W(1.80,825)	W(1.85,785)	W(1.90,745)	W(1.95,705)	W(2.00,665)	W(2.05,625)	W(2.10,585)
	Satisfactory → Poor	W(1.80,798)	W(1.85,758)	W(1.90,718)	W(1.95,678)	W(2.00,638)	W(2.05,598)	W(2.10,558)
	Poor → Very Poor	W(1.75,770)	W(1.80,730)	W(1.85,690)	W(1.90,650)	W(1.95,610)	W(2.00,570)	W(2.05,530)
Size C	Good → Satisfactory	W(1.80,750)	W(1.85,710)	W(1.90,670)	W(1.95,630)	W(2.00,590)	W(2.05,550)	W(2.10,510)
	Satisfactory → Poor	W(1.80,725)	W(1.85,685)	W(1.90,645)	W(1.95,605)	W(2.00,565)	W(2.05,525)	W(2.10,485)
	Poor → Very Poor	W(1.75,700)	W(1.80,660)	W(1.85,620)	W(1.90,580)	W(1.95,540)	W(2.00,500)	W(2.05,460)
Size D	Good → Satisfactory	W(1.80,750)	W(1.85,710)	W(1.90,670)	W(1.95,630)	W(2.00,590)	W(2.05,550)	W(2.10,510)
	Satisfactory → Poor	W(1.80,725)	W(1.85,685)	W(1.90,645)	W(1.95,605)	W(2.00,565)	W(2.05,525)	W(2.10,485)
	Poor → Very Poor	W(1.75,700)	W(1.80,660)	W(1.85,620)	W(1.90,580)	W(1.95,540)	W(2.00,500)	W(2.05,460)
Size E	Good → Satisfactory	W(1.80,750)	W(1.85,710)	W(1.90,670)	W(1.95,630)	W(2.00,590)	W(2.05,550)	W(2.10,510)
	Satisfactory → Poor	W(1.80,725)	W(1.85,685)	W(1.90,645)	W(1.95,605)	W(2.00,565)	W(2.05,525)	W(2.10,485)
	Poor → Very Poor	W(1.75,700)	W(1.80,660)	W(1.85,620)	W(1.90,580)	W(1.95,540)	W(2.00,500)	W(2.05,460)
Size F	Good → Satisfactory	W(1.70,675)	W(1.75,635)	W(1.80,595)	W(1.85,555)	W(1.90,515)	W(1.95,475)	W(2.00,435)
	Satisfactory → Poor	W(1.60,653)	W(1.65,613)	W(1.70,573)	W(1.75,533)	W(1.80,493)	W(1.85,453)	W(1.90,413)
	Poor → Very Poor	W(1.60,630)	W(1.65,590)	W(1.70,550)	W(1.75,510)	W(1.80,470)	W(1.85,430)	W(1.90,390)
Size G	Good → Satisfactory	W(1.70,608)	W(1.75,568)	W(1.80,528)	W(1.85,488)	W(1.90,448)	W(1.95,408)	W(2.00,368)
	Satisfactory → Poor	W(1.60,587)	W(1.65,547)	W(1.70,507)	W(1.75,467)	W(1.80,427)	W(1.85,387)	W(1.90,347)
	Poor → Very Poor	W(1.60,567)	W(1.65,527)	W(1.70,487)	W(1.75,447)	W(1.80,407)	W(1.85,367)	W(1.90,327)
FD Crossing	Good → Satisfactory	W(1.80,750)	W(1.85,710)	W(1.90,670)	W(1.95,630)	W(2.00,590)	W(2.05,550)	W(2.10,510)
	Satisfactory → Poor	W(1.80,725)	W(1.85,685)	W(1.90,645)	W(1.95,605)	W(2.00,565)	W(2.05,525)	W(2.10,485)
	Poor → Very Poor	W(1.75,700)	W(1.80,660)	W(1.85,620)	W(1.90,580)	W(1.95,540)	W(2.00,500)	W(2.05,460)

Table 5. Number of failures, failures per year & component failure rate.

Component	Switch type	Known failures	Adjusted number of failures	Mean number of failures per year, λ	Component failure rate, (Day^{-1})
Stock Rail	Unknown	1018.5	-	-	-
	A	22.5	36	0.011	2.69$*10^{-5}$
	B	108.0	174	0.005	1.27$*10^{-5}$
	C	567.0	911	0.009	2.35$*10^{-5}$
	D	172.5	277	0.008	2.18$*10^{-5}$
	E	108.0	174	0.006	1.73$*10^{-5}$
	F	30.0	48	0.005	1.41$*10^{-5}$
	G	31.5	51	0.010	2.65$*10^{-5}$
	FD	43.5	70	0.010	2.73$*10^{-5}$
Switch Rail	Unknown	9567	-	-	-
	A	141.0	289	0.087	2.37$*10^{-4}$
	B	531.0	1417	0.038	1.04$*10^{-4}$
	C	4222.5	5845	0.055	1.51$*10^{-4}$
	D	591.0	1385	0.040	1.09$*10^{-4}$
	E	927.0	1402	0.051	1.40$*10^{-4}$
	F	196.5	397	0.043	1.16$*10^{-4}$
	G	294.0	345	0.066	1.81$*10^{-4}$
	FD	n/a	n/a	n/a	n/a
Crossing	Unknown	600	-	-	-
	A	10.0	24	0.015	3.99$*10^{-5}$
	B	37.0	88	0.005	1.32$*10^{-5}$
	C	92.0	219	0.004	1.15$*10^{-5}$
	D	149.0	354	0.021	5.71$*10^{-5}$
	E	35.0	83	0.006	1.70$*10^{-5}$
	F	24.0	57	0.013	3.42$*10^{-5}$
	G	14.0	33	0.013	3.57$*10^{-5}$
	FD	75.0	178	0.052	3.56$*10^{-5}$
Check & Wing Rail	Unknown	80	-	-	-
	A	2.0	5	0.0028	7.77$*10^{-6}$
	B	20.0	45	0.0025	6.96$*10^{-6}$
	C	19.0	43	0.0008	2.32$*10^{-6}$
	D	4.0	9	0.0005	1.49$*10^{-6}$
	E	7.0	16	0.0012	3.31$*10^{-6}$
	F	1.0	2	0.0005	1.39$*10^{-6}$
	G	0.5	1	0.0005	1.24$*10^{-6}$
	FD	10.0	23	0.0068	1.85$*10^{-5}$

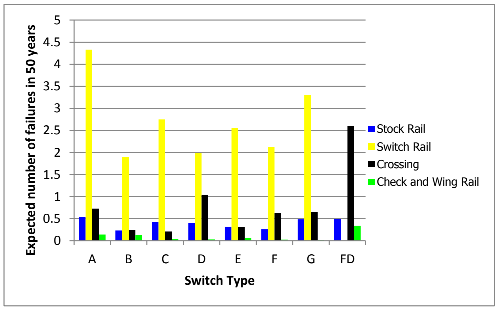

Figure 4. Expected number of failures in 50 years for various components and switch sizes.

Maintainability

Once the component reliability had been determined the second part of the availability assessment was to determine the maintainability. The maintainability is modelled in two parts:

(i) *Schedule time* This is the time between the maintenance being requested and maintenance being complete,

(ii) *Completion time* This is the time the engineers are on site completing the maintenance.

These values are recorded directly in each maintenance record. Once again Weibull++ was used to apply the maximum likelihood method to fit distributions to these data sets. For the check and wing rail, as there were so few records, it was decided to group the records into a single cohort; the schedule time distribution (days) calculated was $W(0.48, 118.4)$ and the completion time distribution (hours) found was $W(1.30, 8.25)$. The stretcher bar maintenance records were recorded in a slightly different way making it more difficult to assign the stretcher bar records to a switch size, it was again decided therefore to treat the records as a single cohort. The schedule distribution (days) found was $L(3.28, 1.90)$ and the completion time distribution (hours) found was $W(1.02, 6.57)$. The distributions found for the remaining maintenance interventions are shown in Table 6. Tamping and stoneblowing are forms of ballast intervention[8], and grinding and reprofiling are used to repair the stock and switch rails.

Inspection intervals The deterioration of any S&C component will generally be unrevealed and therefore it is critical to inspect the S&C regularly to ensure that any deterioration is discovered in a timely manner. Different components will require different inspection types. For example it will generally be possible to visually see missing or defective fastenings, however rail defects are generally not visible to the naked eye. Three types of inspection are used at S&C units. Visual inspections which are used for bearers, fastenings, slide chairs and stretcher bars. Ultrasonic inspections which are used for the rails and lastly geometry /recording car inspection, which is used to assess the track geometry and determine if any ballast maintenance is required.

As a modelling simplification, it is assumed that the inspection frequency is independent of the component condition, and as such the deterioration rate is not influenced by the inspection interval, this is thought to be justified as the inspection frequency is significantly smaller than the degradation rate. The visual inspection frequency assumed is seven days based on Network Rail Standards[33]. The ultrasonic inspection frequency is 28 days based on Network Rail Standards[34]. Lastly, the recording car inspection frequency was assumed to be 56 days according to the information in Network Rail Standards[35].

Summary & Conclusions

This paper presented a reliability study of railway S&C. The paper considered the nine key components within an S&C, and provided a methodology to model degradation, failure, inspection and repair of those nine components. Based on the component properties a mixture of discrete and continuous probability distributions were determined to approximate the four processes outlined. The analysis was further divided by switch type, to allow the impact of switch type to be understood.

It was concluded that switch size impacted the number of replacements with larger switch sizes generally seeing more maintenance interventions. However, switch size did not seem to influence the expected number of failures in a given period.

Due to the complex nature of the interactions between degradation, failure, inspection and maintenance, it is not possible to analytically determine the availability of each component and the overall availability of the S&C. To determine the availability a simulation based approach such as a Markov or Petri net approach would be required, a Petri net solution based on the distributions found in this paper is presented in the companion paper[6].

Notes

1. There are only a very small number of Size H turnout units and as such there was not enough data to make informed conclusions, therefore they are excluded from this study.
2. Previous analysis has shown that less than 1% of interventions take place from 'Super red'[36], as such the 'Super red' band is not considered in this study.

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Table 6. Distributions for the time to schedule maintenance (days) and complete maintenance (hours) for various maintenance tasks.

Type		Maintenance Task						
		Tamping	Stoneblowing	Bearer Replacement	Crossing Repair	Replace Fastening	Slide Chair Repair	Grinding and Re-profiling
Size A	Schedule	W(0.56, 82.23)	n/a	L(3.13, 1.92)	L(2.77, 1.86)	L(2.98, 1.42)	L(3.12, 2.23)	L(2.98, 2.04)
	Completion	W(1.91, 2.23)	n/a	W(1.14,5.55)	L(1.55, 0.90)	E(0.22)	W(8.10, 0.95)	W(4.23 1.32)
Size B	Schedule	L(2.88, 2.03)	L(1.43, 6.44)	W(1.81, 3.55)	L(3.03, 1.94)	L(2.90, 1.71)	W(0.63, 201.5)	L(3.15, 1.79)
	Completion	W(1.38, 1.97)	L(0.35, 0.01)	W(1.69, 7.87)	W(1.19, 7.23)	L(0.33, 1.45)	W(0.78, 6.30)	L(0.95, 0.95)
Size C	Schedule	L(3.36, 1.95)	L(2.32, 1.45)	L(3.50, 1.68)	L(3.08, 1.90)	L(2.84, 1.53)	L(4.09, 2.12)	L(2.96, 1.75)
	Completion	W(1.00, 2.44)	W(0.77, 2.04)	W(1.13, 7.88)	W(1.38, 7.17)	L(0.08, 1.45)	W(0.97, 6.41)	L(0.95, 1.03)
Size D	Schedule	L(3.32, 2.04)	L(2.13, 1.34)	L(3.31, 1.67)	L(3.11, 1.96)	L(2.87, 1.59)	L(3.77, 2.17)	L(3.09, 1.80)
	Completion	W(1.04, 2.12)	W(0.86, 3.33)	L(1.63, 1.01)	W(1.37, 6.82)	L(0.20, 1.36)	W(0.99, 6.94)	L(0.99, 0.99)
Size E	Schedule	L(2.95, 1.95)	L(2.01, 1.12)	L(3.24, 1.72)	L(2.91, 1.81)	L(2.95, 1.61)	L(3.71, 2.33)	L(2.93, 1.79)
	Completion	W(1.19, 2.59)	W(0.60, 1.72)	W(1.11, 7.29)	W(1.29, 7.61)	L(0.20, 1.46)	L(1.40, 0.98)	L(0.92, 1.04)
Size F	Schedule	L(2.82, 1.72)	W(2.46, 4.48)	L(3.23, 1.57)	L(3.21, 1.85)	L(2.62, 1.55)	W(0.55, 218.9)	L(2.97, 1.65)
	Completion	W(1.11, 2.55)	W(0.43, 2.73)	E(0.15)	W(1.54, 7.84)	L(0.23, 1.54)	L(1.29, 1.15)	L(0.99, 0.87)
Size G	Schedule	L(2.97, 1.68)	W(2.46, 4.48)	L(2.97, 1.40)	L(2.80, 1.78)	L(3.14, 1.56)	W(1.41, 355.7)	L(2.87, 1.53)
	Completion	W(1.23, 2.61)	L(2.17, 0.93)	L(1.18, 1.17)	W(1.60, 8.75)	W(0.79, 3.15)	W(0.84, 3.25)	L(0.97, 1.01)
FD	Schedule	L(2.37, 1.46)	n/a	L(2.47, 1.22)	L(3.84, 1.96)	L(3.34, 1.91)	W(0.74, 133.3)	L(3.20, 1.83)
	Completion	W(1.12, 1.25)	n/a	L(1.16, 11.77)	L(1.42, 0.76)	W(0.79, 5.57)	W(2.09, 4.51)	L(0.83, 0.87)

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