The impact of summer heatwaves on railway track geometry maintenance

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Abstract

Elevated summer temperatures are a disrupting factor on the rail network. Due to the risk of a track buckling under thermal expansion forces, geometry maintenance must be delayed during heatwaves, leading to an overall decreased network availability and reliability. Track asset management support tools are used to plan and schedule a variety of maintenance activities, with tamping and stoneblowing being the primary activities for geometry maintenance. No management tools seen in the literature consider the influences of weather on the scheduling and delivery of maintenance. This paper describes a Petri net modelling approach to railway track asset management. This is demonstrated to be a highly flexible method able to capture the complexities of degradation, inspection, and maintenance, and predict the evolution of track geometry quality over time. Different maintenance strategies are tested, varying the degradation thresholds, inspection intervals, policy decisions, and maintenance response times. Excessively hot weather is introduced as an inhibiting factor for all maintenance activities, resulting in extended periods where interventions are delayed. Simulation results show that frequent inspection and timely maintenance scheduling strategies could be followed to attain a highly performing and resilient track system. This asset management support tool could be added to the suite used by the rail industry, providing guidance on maintenance policy through a summer season where heatwave disruptions are expected.

Keywords

Climate change, Degradation model, Heatwave, Maintenance, Petri net model, Railway track degradation, Tamping, Track geometry degradation

Introduction

Maintenance of railway track geometry is an important and year-round process to ensure a safe and comfortable journey for all rail users. A variety of asset management support tools are available to the rail industry¹; these provide guidance on the effective planning and delivery of maintenance works. Despite this variety, there is no consideration seen in the literature toward the effect of extreme weather events on asset management processes. One such weather event is the summer heatwave, which is known to annually disrupt the delivery of maintenance activities in the UK rail network^{2,3}. There is therefore an opportunity to model the impacts of summer heatwaves and assess maintenance strategies for these conditions. The results of this study should marry with existing asset management tools, providing additional guidance when heatwave disruptions are expected.

Track geometry and maintenance

Establishing the condition of the railway track is an essential first step in an asset management strategy. Track geometry deteriorates continuously through its lifetime, as the system is subject to traffic loading and environmental pressures. The condition of track geometry is measured in three dimensions by an instrumented vehicle – the Track Recording Unit (TRU) – travelling around the network, periodically inspecting

the rails over which it travels. This provides parameters of vertical and lateral alignment, gauge, twist, and smoothness, among others. The standard deviation of the averaged vertical geometry over a 35 m length is considered the most significant by many^{4–7}. The vertical geometry shows good correlation with ride quality and is readily recovered using the identified maintenance activities⁸.

Good track condition, with geometry measuring closer to the designed parameters, provides good ride comfort and safety for rail users. The network can be used to full capacity, in terms of traffic speed and volume. Alternatively, poor geometry – further from the design – presents an elevated safety risk of a vehicle derailling³. Extremely poor condition can necessitate enforcing a speed restriction or even a closure, and require maintenance to restore the geometry before returning to capacity.

The condition of track geometry is strongly tied to the underlying support structure⁹. The majority of modern track systems are ballasted; using hard angular stone as a bed to support and stabilise the railway sleepers and the attached rails⁸. As traffic passes, the loads applied are transmitted to the ballast particles, leading to settlement, frictional wear, and breakage, which cause

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the track geometry to deform. When a degraded track condition is detected, a maintenance intervention will be scheduled to restore geometry. The goal is to re-pack or replace material in the ballast bed, and correctly support the track sleepers. The primary maintenance options available are tamping and stoneblowing¹⁰.

Tamping machines lift the rails into the correct geometry position and pack the ballast around the sleepers. Vibrating tines are inserted either side of the sleeper and then squeeze together to move the ballast material. The insertion of the tines does however cause damage of the ballast material, breaking-up the stones, and degrading the condition of the ballast. Whilst the track geometry is initially improved, the damage to the ballast means that the geometry degrades at an increased rate thereafter⁷. Successive tamping operations will therefore reduce in effectiveness. Life-cycle optimisation could define a limit on the number of tamping interventions which may be carried out on a section of ballast, before renewal¹¹.

Stoneblowing is an alternative maintenance action, which involves adding small stone chips to fill the voids around the lifted sleepers. As stoneblowing does not disturb the existing, compacted ballast bed, it does not cause the breakage that is inherent with tamping. Stoneblowing can therefore produce very durable results. However, as stoneblowing does add small particles to the ballast foundation, tamping should not be performed afterwards as the smaller stones will cause secondary problems for drainage of the track bed^{7,12}. Selecting the appropriate maintenance action, as well as correctly timing the activities for optimal performance is the task of asset management support tools.

Influence of high temperature

Elevated summer temperatures can put the rails under considerable longitudinal compressive force as they expand against their fixings¹³. The modern standard continuously welded rail can lengthen by up to 10 mm over a 28 m length on a hot summer's day¹⁴. This compressive force may release by the rail buckling; a sudden lateral deviation of the rail from the designed path, with a high potential to derail a train. Correctly maintained ballast should however provide sufficient support strength to keep the rails in position.

The identified ballast maintenance activities are however involved processes that require lifting the rails into the correct alignment. This action would provide a heated rail the freedom to buckle and cause a greater maintenance problem than was originally sought to repair. As such, maintenance must be delayed until the rails have cooled sufficiently. It is identified that over 20 % of possible working days are lost during a modern summer, with projections of two- to three-times as many “non-working” days expected by the 2040s¹⁵. With the onset of climate change and the resultant increasing temperatures, long periods of hot weather are becoming more prevalent, and maintenance strategies will need to be adapted to account for the restrictions to maintenance schedules.

Nonetheless, there are few existing studies into the effects of high temperatures on the rail network infrastructure. Known issues include the overheating of electrical equipment, and the health and safety of both staff and passengers, though most do focus on rail buckling as the ultimate failure condition brought on by hot weather^{13,16–18}. Two publications by Dobney et al.^{16,17} assess the impacts of summer heatwaves in causing rail buckles and therefore network delays. Historical data from the UK south-east shows that severe buckles have occurred at temperatures as low as 25 °C – in contrast to the Network Rail quoted 32 °C limit³ – revealing a rail network that has low resilience to hot weather. It is estimated that heat-related delays cost managers between £3m and £15m per year during modern summers, and predict up to £28m annually in 50 years time, under various climate change predictions. They conclude however that “ensuring the track is thoroughly maintained would reduce the vulnerability of the rail during hot weather”¹⁶.

Asset maintenance modelling

Track asset management is a complex problem, combining track geometry condition, degradation, inspection, and maintenance into an effective strategy. Modelling is therefore highly advantageous in representing these different processes in a maintenance planning tool. Because of inherent uncertainty in track behaviour characteristics, two otherwise identical sections may show entirely different degradation and recovery^{1,10}. Statistical models are frequently employed in such problems, for their robust ability to predict behaviour following previous observations, whilst accounting for variability using probability. These models do require sufficient historical records to define the time distribution which describes the behaviour¹⁹.

Stochastic processes capture the unpredictability of the degradation evolution, with methods such as the Gamma process^{20,21}, Gaussian random process²², or Dagum distribution^{23,24} being fit to data which represents the measured vertical track geometry continuously with time. These processes follow the monotonic nature of damage accumulation in the ballast.

Other classes of statistical models are Markov chains and Markov processes. A Markov model follows the transition between different condition states, representing the degradation process in an exponential distribution²⁵. Condition states are defined by discretised track geometry measurements, or other classes of track quality²⁶. There are however two assumptions in a Markov model that limit their effectiveness in representing the track degradation process as it is currently understood; that transition probabilities are constant, and that future states depend only on the current state. As the track degradation is observed to be dependent on the maintenance history (particularly tamping activities) the size of the Markov model grows dramatically to represent all possible transition rates⁴.

An alternative model solution to overcome these limitations is the Petri net (PN) approach. PNs are capable of modelling complex systems with concurrencies and dependencies in a graphical description. The PN simulation is a stochastic technique which accepts any distribution for transition times, and so can provide greater detail in modelling degradation, inspection, and maintenance than comparable techniques²⁷.

Petri nets have been used to great success for several track asset management studies^{10,27–30}. Common features among these models includes the use of the Weibull distribution, which best fits the observed degradation rate data⁷. Also, a modular approach is followed to describe the combination of different system processes^{10,29}. The technique has been extended with advanced transition types, such as the conditional transition²⁸ which allows for the dependency of degradation rate on maintenance history.

This study contributes a Petri net model for geometry maintenance of a railway track section and an experimental methodology for investigating a series of variant asset management strategies. Results are compared for the track section availability, major degradation conditions, and lifetime maintenance volumes. This provides an indication of performance expected during fair weather, and subsequently through a series of heatwave events.

Track Section Model

This section introduces the stochastic Petri net methods which are employed to model the management of a single one-eighth mile track section (approximately 200 m). The one-eighth mile unit is the standard track section length used in the UK rail network for data collection and asset management planning. The model describes the degradation of the rail geometry, its inspection, and maintenance activity. A “hot weather” module is added to investigate the impacts of this disruption. Parameters are defined where simulations will be varied to compare different strategies. Through simulation, the results give an indication of the time that the modelled system is expected to be in each condition state, and the amount of maintenance that is required over an asset lifetime. This is used to compare variant strategies, in order to make recommendation on more optimal approaches.

Petri Net Modelling

The Petri net is a bipartite graph of places, representing system states, and transitions, defining the time delays between state changes. These are represented graphically as circles and rectangles respectively. Directed arcs link places to transitions, and transitions to places. Examples of these PN elements can be seen in figure 1.a).

The places may be “marked” by tokens, to represent a system-state being active or true. The tokens move through the PN as dictated by the firing of transitions, as the simulated system changes from one state to another. Thus, the Petri Net model can represent dynamic system behaviours.

Figure 1. a) Petri net elements; b) example Petri net

Transitions are defined with the time between events occurring in the model. Transition times may be zero for instant actions, a fixed delay, or calculated using probabilistic distributions and random sampling. This is where the stochastic process is introduced in the simulation method.

Two transitions with non-standard functions are utilised in the model. The periodic transition is used for events which occur at regular intervals. These will attempt to fire at fixed intervals, instead of a timing being initiated by a prior event or marking. Another is the routing transition. This will select a single output from multiple connected places, based on probabilistic ratios defined in the PN generation. The routing transition can be used to represent a decision being made among multiple possible outputs.

Places are connected to transitions as either inputs or outputs, as indicated by the direction of the arcs. For a transition to fire it must be enabled by having all its input places marked by tokens. In firing, tokens are removed from all the transition input places and added to all the output places. An arc has a multiplicity associated with it, defining how many tokens are required as an input, or provided at an output; by default, arcs have a multiplicity of one.

Other arc types allow the PN to model different behaviours. An inhibit arc prevents a transition from firing whilst the connected state is marked. A reset arc is used to remove all the tokens from a place in the net. The conditional arc indicates a transition time which has a dependency on another system state.

Figure 1.b) shows an example of Petri net function. Place $P1$ is the input to transition $T1$, and it is marked meaning $T1$ is enabled; the transition time t is conditional on the marking of place $P2$. After time t has passed $T1$ will fire, removing the token from its input place $P1$ and placing a token in its output place $P3$. The marking in $P2$ is maintained, and it continues to define transition time t . Place $P4$ is reset by the firing of transition $T1$, and all the tokens are removed. Finally, the arc between $P3$ and $T1$ is also an inhibitor, meaning transition $T1$ will not fire if $P1$ is marked again, until the token is removed from $P3$. To remove visual clutter, the output and inhibitor arcs between $T1$ and $P3$ are

combined into a “double-ended” arc, but otherwise the functions remain separate.

Track section model structure

Figure 2 shows the track section Petri net model, with the initial marking at the start of the lifetime simulations. The places are labelled to indicate the management process. The transitions are coded into groups: D for degradation; I for inspection; P for policy; S for decision; M for maintenance completion; W for weather cycles. The following describes the modular structure, with reference to the labelled PN elements in the figure.

Degradation process Five condition states have been defined to represent thresholds in the track vertical geometry deviation measurements. The conditions and thresholds are; *good* condition close to the perfect geometry, 0 mm deviation; *poor* when threshold σ_{Poor} is

Figure 2. Full track section Petri Net model

Table 1. Weibull parameters used in degradation transitions

Number of tamps	D1 0 - 1.9 mm		D2 1.9 - 2.7 mm		D3 2.7 - 3.4 mm		D4 3.4 - 5 mm	
	η (days)	β	η (days)	β	η (days)	β	η (days)	β
0	2701.6	0.950	1044.3	0.299	4674.9	0.296	2240.1	0.372
1	2224.3	0.996	2222.3	0.351	3653.7	0.311	3542	0.361
2	2199.8	1.108	10105	0.316	3008.7	0.308	1116.4	0.455
3	2080	1.147	7947.2	0.310	2363.6	0.314	1679.7	0.426
4	2025	1.195	11767	0.312	2240.1	0.311	1352.2	0.447
5	1970	1.245	6932.3	0.299	2497.8	0.305	1746.6	0.438
6	1915	1.295	14602	0.273	2967.5	0.29	1733.6	0.441
7	1770	1.390	35174	0.273	9682.6	0.264	1449	0.419

Number of tamps	D1 0 - 1 mm		D1 0 - 2 mm		D2 1 - 2 mm		D2 2 - 3 mm	
	η (days)	β	η (days)	β	η (days)	β	η (days)	β
0	2500	0.860	2724	0.960	61.959	0.420	406.23	0.560
1	2200	0.960	2227	1.000	54.34	0.310	429.57	0.610
2	2000	1.000	2222	1.120	75.847	0.450	406.87	0.600
3	1900	1.120	2100	1.150	82.06	0.460	320.39	0.600
4	1800	1.150	2050	1.200	108.62	0.500	303.45	0.600
5	1700	1.200	2000	1.250	149.93	0.540	178.02	0.540
6	1600	1.250	1950	1.300	190.08	0.580	88.059	0.470
7	1500	1.300	1800	1.400	136	0.550	69.428	0.460

Number of tamps	D2 1 - 3 mm		D3 2 - 3.4 mm		D3 3 - 3.4 mm	
	η (days)	β	η (days)	β	η (days)	β
0	580.24	0.640	607.45	0.630	61.675	0.390
1	450.65	0.620	641.65	0.680	73.329	0.410
2	517.75	0.650	518.19	0.660	57.546	0.410
3	464.4	0.660	406.74	0.640	49.418	0.410
4	476.94	0.670	352.76	0.620	41.985	0.410
5	413.26	0.690	263.7	0.590	35.211	0.400
6	354.46	0.680	150.82	0.530	24.348	0.380
7	277.46	0.650	114.08	0.500	17.342	0.360

exceeded and routine maintenance should be scheduled; *critical* exceeding σ_{Crit} , when maintenance is needed urgently, but otherwise the section is fully open to traffic; a major degradation condition where a *speed restriction* is enforced when safety limit σ_{SR} is exceeded; and the major degraded state imposing a *closure* for any measurement beyond σ_{Close} . These descriptors are used for clarity in the model, and reflect Network Rail's standardised approach to geometry maintenance. All the simulation runs are initiated from the *good* condition, as indicated by the token in figure 2.

Degradation transitions D1 – 4 connect the condition places and dictate the progression from better to worse states. The time delays for each transition follow Weibull probability distributions, with parameters fit to empirical data. Weibull parameters were found to provide the best fit for the provided Network Rail national measurement database. Detail can be found in publications by Audley and Andrews⁷, and Andrews²⁸. The degradation transitions are conditional on the maintenance history of the track section, changing the distribution parameters used; conditional arcs connect places which count the *number of tamps* ($\#T$) and *number of stoneblowings* ($\#SB$) to the transitions. Successive tamping operations will increase the rate of degradation, whilst stoneblowing will maintain the same parameters⁸.

The condition thresholds and degradation rates have been modelled for the highest track quality, where vehicle speeds are in excess of 100 mph. This track class has the greatest requirement for good quality rail geometry, and the greatest impact on network safety in the event of a failure. The thresholds for the *speed restriction* and *closure* conditions are required safety limits defined in the standard for this track class³. These are $\sigma_{SR} = 3.4 \text{ mm}$ and $\sigma_{Close} = 5.0 \text{ mm}$.

Recommended thresholds for the *poor* and *critical* track geometry conditions are $\sigma_{Poor} = 1.9 \text{ mm}$ and $\sigma_{Crit} = 2.7 \text{ mm}$. These values are used for the base case scenario. These thresholds can however be changed as part of the variant management strategy study. If they are reduced, then maintenance will be performed earlier in the lifetime of the track section, though the total maintenance volume is likely to grow. If they are increased, closer to the speed restriction threshold, then it is expected that routine maintenance opportunities may be missed, and the major degradation states will be reached more frequently.

The degradation transition times D1 – 4 are calculated from two-parameter Weibull probability distributions, with parameters β the shape factor, and η the characteristic lifetime in days. Table 1 lists the Weibull parameters that are used in the simulations, including variant strategies where $\sigma_{Poor} = 1.0 \text{ mm}$ or 2.0 mm , and $\sigma_{Crit} = 2.0 \text{ mm}$ or 3.0 mm . These degradation

distributions have been calculated using the convolution method presented by Andrews²⁸.

Inspection process The degradation process represents the unrevealed condition of the track section in situ. The state is not known to the asset management process until a measurement is made by the TRU vehicle traveling around the network on an inspection schedule. This knowledge acquisition is modelled by four inspection transitions $I1 - 4$, and four *knowledge places*, $K.Poor$, $K.Crit$, $K.SR$, and $K.Close$ – an inspection of a *good* condition is trivial as there is no associated maintenance action, so this is omitted.

When the inspection is performed whichever track condition is true becomes “known”, and the corresponding *knowledge place* will be marked. The marking in the track condition place is replaced such that the degradation process may continue. A marking in a *knowledge place* inhibits the associated inspection transition, to prevent a duplication at the next inspection.

The inspection transitions are all timed at intervals of θ . A typical interval between inspections for a high quality, highly utilised track would be once monthly, or $\theta = 30$ days in the base case. This will be varied to shorter time intervals, to monitor the degradation more closely, or extended to longer periods, potentially without decreasing overall performance. Inspection intervals are tested for θ values of 7 days, 14 days, and 60 days.

Maintenance policy Once the condition of the track section is known, a maintenance activity can be selected and scheduled. There are two timelines for maintenance considered in this model. Routine maintenance is planned in the future for a *poor* rail condition, and urgent maintenance must be completed immediately when a *critical*, *speed restriction*, or *closure* condition is detected. The difference is that a poor track condition can be tolerated for a time, as traffic continues to pass at full volume, whilst the major degradation states and disruptions should be corrected quickly. For each of the maintenance timelines, either a tamping or stoneblowing activity is selected to complete the works.

Policy transitions $P1 - 4$ are instant transitions, as the asset management will act immediately on the known track condition. These transitions lead to either a *routine* maintenance request place or an *urgent* maintenance request place.

From the request places, a maintenance selection is made by decision transitions $S1$ and $S2$. These are probabilistic routing transitions, which select one of the two possible output places on firing. In practice, maintenance engineers will select between tamping or stoneblowing as is appropriate to the track section, however trends can be found in maintenance records to simply represent this decision as a ratio³⁰. Decision transitions are defined with either *routine tamping : routine stoneblowing* $R.T : R.SB$, or *urgent tamping : urgent stoneblowing* $U.T : U.SB$.

As has been identified, tamping activities should not be performed after stoneblowing, as the smaller stone particles would lead to secondary problems on

the section. Thus, the decision transitions $S1$ and $S2$ also have a dependency to the stoneblow counting place $\#SB$. As long as this place is marked with at least one token, the defined ratios are superseded, and all maintenance decisions go to stoneblowing; i.e. $R.T : R.SB = U.T : U.SB = 0 : 1$. Both $S1$ and $S2$ are instant transitions with $t = 0$, as the maintenance activity decision is made immediately along with the maintenance time schedule.

In the UK network tamping is strongly preferred for routine maintenance³⁰, though stoneblower usage increases for the major degradation conditions as it shows good results when the geometry recovery requirement is larger³¹. For the base case simulation, the routine ratio *routine tamping : routine stoneblowing* is defined as 9.5 : 1 and the urgent ratio *urgent tamping : urgent stoneblowing* is 3 : 1. The variations will use $R.T : R.SB = 3 : 1$ or $1 : 0$, and $U.T : U.SB = 1 : 1$, testing whether different maintenance mixes influence the future degradation behaviours.

Maintenance completion With the selection of maintenance works (*routine tamping*, *routine stoneblowing*, *urgent tamping*, or *urgent stoneblowing*) that activity must be scheduled and completed to restore the track geometry condition. Maintenance transitions $M1 - 4$ represent the time schedule for each activity respectively. This is a combination of the work scheduling and completion time.

Following the arcs in figure 2, when any of the maintenance transitions fire, the track is returned to the *good* condition state. All track condition, knowledge, and maintenance request places are reset (these arcs are not shown in the figure for clarity). The appropriate transitions will also mark the *number of tamps* ($\#T$) and *number of stoneblows* ($\#SB$) counting place; their marking is never reset. With the maintenance process complete, the track section degradation modelling continues anew. However, with maintenance history being counted, the track behaviour will change from one cycle to the next.

All four maintenance transitions $M1 - 4$ follow normal probability distributions; grouped into the two timelines, the transition times defined by $F_{routine}$ or F_{urgent} . The mean μ is the target response time in days, whilst the variance in the work programmes is accounted for in σ^2 . For the base case, routine maintenance will be planned for approximately three months’ time, with $F_{routine} = N(90, 15)$. The variations test quicker or slower response times; one month $F_{routine} = N(30, 15)$, two months $F_{routine} = N(60, 15)$, and six months $F_{routine} = N(180, 15)$. Urgent maintenance is of such great importance that the demanded action should be completed on the same day, with $F_{urgent} = N(0.5, 0.5)$ in all cases.

Temperature exceedances Weather effects are modelled as a simple loop between two states, *fair* or *hot*. Two criteria are metered by Network Rail to define too-hot weather; when rail temperatures exceed 32 °C or will exceed 38 °C within 3 days (an air temperature of 21 °C and 25 °C respectively)¹⁵. Assuming this is correctly

applied, all maintenance activities are suspended until the rails have cooled sufficiently, and the heatwave is ended. This definition considers only that the critical rail temperature threshold is exceeded, not to what degree.

Weather transitions $W1$ and $W2$ are respectively the periods between heatwaves τ_{fair} , and their durations τ_{hot} . When the *hot* weather place is marked, all maintenance transitions $M1 - 4$ are inhibited from firing. The incidence of a heatwave event only has bearing on the delivery of maintenance in this model. The token in the *fair* place may be omitted from the model to test lifetime performance without the heatwave disruption.

The result of this interaction is that, although a maintenance activity may be due – or urgently required – the hot weather prevents completion of the work until the rail has cooled sufficiently. This may lead to longer periods of *speed restrictions* or *closures* being enforced, and more frequent major disruptions as the track condition continues to degrade before maintenance can be performed.

Testing focuses on the impact of a single heatwave event on the track section, in a steady state geometry condition. A range of heatwave durations will be tested. Sufficient time is allowed to elapse such that the model has settled away from the initial 100 % *good* marking for all variant strategies. Test scenarios will then follow $\tau_{hot} = \{1, 2, 3, 4, 5, 10, 15, 20, 25, 30\}$ days to test the performance sensitivity. These values describe hot weather events which may be experienced in modern times, as well as longer duration events that are predicted under future climate change³². This will investigate how track condition evolves during a maintenance-free period, and whether asset management strategies can add resilience to mitigate the impact.

Model execution

Simulation follows the Monte Carlo method, with random numbers sampled to calculate the time duration for the transitions which follow probabilistic distributions. The simulation is timed on a day-scale. The initial executions establish the fair weather lifetime performance, without the heatwave token. The strategies which offer benefit over the base case will be carried forward for testing under hot weather disruptions; this is judged on improved availability, reduced “at-risk” time where a major degradation state is unknown, and limiting urgent maintenance volume requirements.

Simulation results and analysis

Fair weather performance analysis

The first series of simulations are completed for a 30-year lifetime, with averaged results converging through 2,000 iterations. The key outputs for comparison are the full capacity availability (time in either *good*, *poor*, or *critical* states, when full traffic volume can pass),

Table 2. Base case strategy parameters

Parameter	Value
Poor threshold	$\sigma_{Poor} = 1.9 \text{ mm}$
Critical threshold	$\sigma_{Crit} = 2.7 \text{ mm}$
Speed restriction threshold	$\sigma_{SR} = 3.4 \text{ mm}$
Close threshold	$\sigma_{Close} = 5.0 \text{ mm}$
Inspection interval	$\theta = 30 \text{ days}$
Routine ratio	$RT : RSB = 9.5 : 1$
Urgent ratio	$UT : USB = 3 : 1$
Routine completion rate	$F_{routine} = N(90, 15)$
Urgent completion rate	$F_{urgent} = N(1, 1)$

the proportion of major degradation conditions (*speed restrictions* and *closures*), and the volume of lifetime maintenance. Table 2 lists the parameter values followed for the base case strategy. Table 3 is a key to the variant management strategies as introduced in the previous section used throughout the results.

Table 4 summarises the fair weather lifetime performance following the base case parameters and each variant strategy. Full capacity is the aggregate time the track is in the *good*, *poor*, or *critical* conditions, where the section is available and traffic can pass at full speed. For the major degradation states, the unknown time represents the at-risk period when vehicles may pass at an unsafe speed because the geometry condition has not yet been inspected. After this inspection, the *speed restriction* or *closure* will be enforced for a time period until the intervention is scheduled and completed. Finally, the volumes of the different maintenance actions are counted over the lifetime.

Geometry thresholds 2 and 3, both with $\sigma_{Crit} = 3 \text{ mm}$, are not suitable candidates to replace the base case approach during fair weather. By setting the critical threshold too close to that for speed restrictions $\sigma_{SR} = 3.4 \text{ mm}$, maintenance is not completed in time before the transition to the worse condition state. This is seen in predicting the shortest availability times, and a significant increase in the unknown time proportions. Geometry threshold 1 is generally comparable to the base case scenario, though with a higher proportion of lifetime stoneblowings expected.

Table 3. Key for variant asset strategy test scenarios

Test scenario	Variant management strategy
Threshold 1	$\sigma_{Poor} = 1 \text{ mm}, \sigma_{Crit} = 2 \text{ mm}$
Threshold 2	$\sigma_{Poor} = 2 \text{ mm}, \sigma_{Crit} = 3 \text{ mm}$
Threshold 3	$\sigma_{Poor} = 1 \text{ mm}, \sigma_{Crit} = 3 \text{ mm}$
Inspection 1	$\theta = 7 \text{ days}$
Inspection 2	$\theta = 14 \text{ days}$
Inspection 3	$\theta = 60 \text{ days}$
Ratio 1	$RT : RSB = 3 : 1$
Ratio 2	$RT : RSB = 1 : 0$
Ratio 3	$UT : USB = 1 : 1$
Schedule 1	$F_{routine} = N(30, 15)$
Schedule 2	$F_{routine} = N(60, 15)$
Schedule 3	$F_{routine} = N(180, 15)$

Table 4. Fair weather averaged lifetime performance results

Simulation	Full capacity time	Speed restrictions			Closures			Tamping		Stoneblowing	
		Unknown time	Enforced time	Enforced number	Unknown time	Enforced time	Enforced number	Routine number	Urgent number	Routine number	Urgent number
Base Case	99.975 %	0.0216 %	0.00095 %	0.200	0.00242 %	0.00011 %	0.028	2.594	0.709	0.601	0.648
Threshold 1	99.972 %	0.0246 %	0.00108 %	0.241	0.00251 %	0.00016 %	0.036	1.261	1.514	0.336	1.603
Threshold 2	99.921 %	0.0695 %	0.00292 %	0.637	0.00662 %	0.00033 %	0.078	2.340	0.962	0.596	0.740
Threshold 3	99.932 %	0.0594 %	0.00244 %	0.517	0.00605 %	0.00029 %	0.067	2.739	0.812	0.798	0.581
Inspection 1	99.996 %	0.0033 %	0.00063 %	0.133	0.00021 %	0.00005 %	0.012	2.687	0.741	0.562	0.602
Inspection 2	99.990 %	0.0082 %	0.00076 %	0.164	0.00091 %	0.00011 %	0.021	2.652	0.753	0.584	0.598
Inspection 3	99.934 %	0.0556 %	0.00105 %	0.219	0.00867 %	0.00018 %	0.043	2.609	0.724	0.584	0.615
Ratio 1	99.975 %	0.0206 %	0.00100 %	0.199	0.00299 %	0.00012 %	0.029	1.561	0.546	1.339	0.868
Ratio 2	99.973 %	0.0229 %	0.00092 %	0.204	0.00261 %	0.00016 %	0.027	2.921	0.801	0.365	0.546
Ratio 3	99.976 %	0.0206 %	0.00084 %	0.194	0.00261 %	0.00015 %	0.015	1.461	0.266	1.373	1.132
Schedule 1	99.983 %	0.0145 %	0.00071 %	0.138	0.00171 %	0.00006 %	0.015	3.163	0.489	0.628	0.440
Schedule 2	99.979 %	0.0187 %	0.00071 %	0.171	0.00194 %	0.00010 %	0.023	2.817	0.640	0.619	0.569
Schedule 3	99.971 %	0.0249 %	0.00105 %	0.222	0.00287 %	0.00013 %	0.033	2.347	0.835	0.492	0.734

Table 5. Predicted condition and maintenance requirements at the end of the heatwave periods following the base case strategy

Base Case	Full capacity number	Speed restrictions			Closures			Tamping		Stoneblowing	
		Unknown time (days)	Enforced time (days)	Enforced number	Unknown time (days)	Enforced time (days)	Enforced number	Routine	Urgent	Routine	Urgent
0 day	99.9467 %	0.000000	0.000000	0.0000 %	0.000000	0.000000	0.0000 %	0.0200 %	0.0000 %	0.0067 %	0.0000 %
1 day	99.9467 %	0.000533	0.000000	0.0000 %	0.000000	0.000000	0.0000 %	0.0400 %	0.0000 %	0.0133 %	0.0000 %
2 day	99.9467 %	0.000533	0.000000	0.0000 %	0.000000	0.000000	0.0000 %	0.0667 %	0.0000 %	0.0333 %	0.0000 %
3 day	99.9467 %	0.000533	0.000000	0.0000 %	0.000000	0.000000	0.0000 %	0.1000 %	0.0000 %	0.0333 %	0.0000 %
4 day	99.9467 %	0.000533	0.000000	0.0000 %	0.000000	0.000000	0.0000 %	0.1333 %	0.0000 %	0.0467 %	0.0000 %
5 day	99.9400 %	0.000427	0.000120	0.0600 %	0.000000	0.000000	0.0000 %	0.1533 %	0.1000 %	0.0467 %	0.0733 %
10 day	99.9333 %	0.000240	0.000360	0.0600 %	0.000000	0.000000	0.0000 %	0.2800 %	0.1533 %	0.0933 %	0.1933 %
15 day	99.9133 %	0.000227	0.000440	0.0600 %	0.000000	0.000000	0.0000 %	0.4333 %	0.1533 %	0.1333 %	0.1933 %
20 day	99.8867 %	0.000267	0.000480	0.0600 %	0.000000	0.000000	0.0000 %	0.5533 %	0.1533 %	0.1600 %	0.1933 %
25 day	99.8800 %	0.000333	0.000504	0.0600 %	0.000000	0.000000	0.0000 %	0.6867 %	0.1533 %	0.2200 %	0.1933 %
30 day	99.8533 %	0.000382	0.000520	0.0600 %	0.000011	0.000000	0.0000 %	0.8000 %	0.1533 %	0.2733 %	0.1933 %

Shorter inspection intervals 1 and 2 give improved performance over the base case, comparing both availability time and the proportions of speed restrictions and closures. These allow for more detailed monitoring of the track section degradation progression, and hence more timely intervention scheduling. This is however at the expense of greater maintenance volumes required in the track section's lifetime, a compromise. The longer inspection interval, $\theta = 60$ days, has worse availability performance than the base case, with longer durations before degraded conditions are detected and corrected.

In a similar fashion, the shorter maintenance schedules 1 and 2 following $F_{routine} = N(30, 15)$ and $N(60, 15)$ have improved availability compared to the base case, thanks to sooner completion of the works. These strategy variations are quicker to act on a *poor* track condition, and so there is a reduced likelihood of reaching the major degradation states. Again, overall maintenance volume is predicted to increase in achieving the higher performance. Following the longer maintenance schedule 3 however means many routine maintenance opportunities are missed before degradation to a major condition, and urgent maintenance is instead scheduled. This is seen in the relative proportions of the two maintenance timelines. A large proportion of urgent maintenance should be avoided as it would be more difficult to deliver effectively.

The different maintenance ratio tests generally give comparable performance to the base case, in terms of capacity availability and major degradation impacts. Ratios 1 and 3 however both predict much higher proportions of urgent stoneblowing activities than the base case. Because Network Rail supports a small fleet of stoneblowing equipment compared to tamping machines – 14 versus 65³³ – this workload intensity may prove difficult to deliver across the full network. Ratio 2 is easier to deliver with the existing equipment and workforce.

Hot weather performance disruptions

The asset management strategies which provide excellent fair weather performance have been carried forward for analysis under hot weather disruptions. These are: degradation threshold 1; inspection interval 2; routine maintenance ratio 2; and routine maintenance schedule 2. These strategies are selected for providing high track system availability, without compromising on greatly increased maintenance volumes. The results from these tests are summarised in tables 6 through 9, along with the base case performance in table 5. The results from the other variant strategies are found in the supplementary data.

The test scenarios follow $\tau_{hot} = \{1, 2, 3, 4, 5, 10, 15, 20, 25, 30\}$ days of heatwave incidence, from the steady state performance (which is labelled as the 0 day result). Resilience is exhibited by retaining high track availability through the maintenance-free periods. The listed maintenance volumes reflect the accumulation of works that are due

and become available for completion at the end of the heatwave, simultaneously.

Table 5 lists the predicted condition of the track section at the end of the 10 heatwave periods, operating under the base case strategy. The shorter durations (up to $\tau_{hot} = 4$ days) have no effect on the 99.9467 % track availability. As the track is already maintained to a high standard, the base strategy is resilient to shorter disruptions.

For heatwave durations from 5 to 30 days, availability diminishes at a rate of 0.0035 % per day. Almost 0.1 % of a given track section population would therefore degrade to a major disruption condition during 30 maintenance-free days, necessitating multiple traffic restrictions across the rail network. At this point 1.42 % of the population has a maintenance action due; an aggregate of the four activities.

The condition threshold 1 strategy has low resilience to the heatwave events. Following this management approach has the greatest loss of availability of the selected variants; 0.0063 % reduction per day though the 10 heatwave tests in table 6. Because of the broader *critical* threshold, a greater proportion of urgent maintenance is required. The 30 day test predicts 0.39 % of track sections requiring urgent tamping, and a further 0.50 % needing urgent stoneblowing, much greater proportions than needed with the base case.

The 14 day inspection interval, half of that used in the base case, provides detailed condition monitoring and delivers high reliability through fair weather. This is seen in table 7, with 100 % track availability at the outset and through the shorter heatwaves, $\tau_{hot} = \{1, 2, 3\}$. High availability is maintained through the maintenance-free period, with the greatest likelihood of remaining at full capacity through the end of 30 days of heatwave.

The increased inspection rate provides the lowest at-risk time where track restriction state is unknown; averaging 0.000143 compared to 0.000382 days for the base case. Very good resilience is shown with no closure conditions in any test period, enforced or unknown.

In table 8 the decision ratio 2 strategy shows the lowest initial availability prediction of those compared, 99.9133 %. However, this is paired with the smallest major degradation rate at 0.0020 % per day. A result of the lower availability values, the ratio 2 strategy predicts the greatest probabilities of disruption with 0.10 % for speed restriction and 0.0067 % for closure through 30 days of hot weather. This strategy therefore provides high resilience for track geometry in the maintenance-free period, with opportunity for improvement in the steady-state conditions.

The final asset management approach compared under the hot weather effects is the shorter routine maintenance schedule 2. Following this strategy provides resilience through the longer duration heatwave periods, with predicted availability in table 9 only decreasing 0.02 % between 10 and 30 days. In traffic restrictions and maintenance volumes this strategy performs very similarly to the base case, with slightly higher proportion of stoneblowings demanded.

Table 6. Predicted condition and maintenance requirements at the end of the heatwave periods following the strategy with condition thresholds $\sigma_{Poor} = 1 \text{ mm}$, $\sigma_{Crit} = 2 \text{ mm}$

Threshold 1	Full capacity number	Speed restrictions			Closures			Tamping		Stoneblowing	
		Unknown time (days)	Enforced time (days)	Enforced number	Unknown time (days)	Enforced time (days)	Enforced number	Routine	Urgent	Routine	Urgent
0 day	99.9667 %	0.000000	0.000000	0.0000 %	0.000000	0.000000	0.0000 %	0.0067 %	0.0000 %	0.0067 %	0.0000 %
1 day	99.9600 %	0.000400	0.000000	0.0000 %	0.000000	0.000000	0.0000 %	0.0267 %	0.0000 %	0.0133 %	0.0000 %
2 day	99.9600 %	0.000400	0.000000	0.0000 %	0.000000	0.000000	0.0000 %	0.0333 %	0.0000 %	0.0200 %	0.0000 %
3 day	99.9467 %	0.000444	0.000000	0.0000 %	0.000000	0.000000	0.0000 %	0.0400 %	0.0000 %	0.0267 %	0.0000 %
4 day	99.9400 %	0.000483	0.000000	0.0000 %	0.000000	0.000000	0.0000 %	0.0400 %	0.0000 %	0.0267 %	0.0000 %
5 day	99.9333 %	0.000387	0.000133	0.0667 %	0.000000	0.000000	0.0000 %	0.0467 %	0.1800 %	0.0267 %	0.2600 %
10 day	99.8933 %	0.000280	0.000400	0.0667 %	0.000013	0.000000	0.0000 %	0.1000 %	0.3933 %	0.0267 %	0.5000 %
15 day	99.8800 %	0.000311	0.000489	0.0667 %	0.000031	0.000000	0.0000 %	0.1333 %	0.3933 %	0.0400 %	0.5000 %
20 day	99.8667 %	0.000377	0.000533	0.0667 %	0.000040	0.000000	0.0000 %	0.1933 %	0.3933 %	0.0800 %	0.5000 %
25 day	99.8133 %	0.000480	0.000560	0.0667 %	0.000045	0.000000	0.0000 %	0.2267 %	0.3933 %	0.1067 %	0.5000 %
30 day	99.7600 %	0.000638	0.000578	0.0667 %	0.000049	0.000000	0.0000 %	0.3000 %	0.3933 %	0.1133 %	0.5000 %

Table 7. Predicted condition and maintenance requirements at the end of the heatwave periods following the strategy with inspection interval $\theta = 14 \text{ days}$

Inspection 2	Full capacity number	Speed restrictions			Closures			Tamping		Stoneblowing	
		Unknown time (days)	Enforced time (days)	Enforced number	Unknown time (days)	Enforced time (days)	Enforced number	Routine	Urgent	Routine	Urgent
0 day	100.0000 %	0.000000	0.000000	0.0000 %	0.000000	0.000000	0.0000 %	0.0333 %	0.0000 %	0.0067 %	0.0000 %
1 day	100.0000 %	0.000000	0.000000	0.0000 %	0.000000	0.000000	0.0000 %	0.0533 %	0.0000 %	0.0133 %	0.0000 %
2 day	100.0000 %	0.000000	0.000000	0.0000 %	0.000000	0.000000	0.0000 %	0.0800 %	0.0000 %	0.0133 %	0.0000 %
3 day	100.0000 %	0.000000	0.000000	0.0000 %	0.000000	0.000000	0.0000 %	0.0933 %	0.0000 %	0.0267 %	0.0000 %
4 day	99.9933 %	0.000017	0.000000	0.0000 %	0.000000	0.000000	0.0000 %	0.1267 %	0.0000 %	0.0267 %	0.0000 %
5 day	99.9867 %	0.000013	0.000027	0.0133 %	0.000000	0.000000	0.0000 %	0.1333 %	0.0267 %	0.0267 %	0.0600 %
10 day	99.9800 %	0.000013	0.000080	0.0133 %	0.000000	0.000000	0.0000 %	0.3067 %	0.0733 %	0.0667 %	0.0933 %
15 day	99.9600 %	0.000071	0.000098	0.0133 %	0.000000	0.000000	0.0000 %	0.4000 %	0.0733 %	0.1067 %	0.0933 %
20 day	99.9400 %	0.000100	0.000153	0.0600 %	0.000000	0.000000	0.0000 %	0.5267 %	0.1533 %	0.1267 %	0.1667 %
25 day	99.9267 %	0.000104	0.000237	0.0600 %	0.000000	0.000000	0.0000 %	0.6533 %	0.1667 %	0.1600 %	0.1667 %
30 day	99.9067 %	0.000143	0.000287	0.0600 %	0.000000	0.000000	0.0000 %	0.8133 %	0.1667 %	0.2000 %	0.1667 %

Table 8. Predicted condition and maintenance requirements at the end of the heatwave periods following the strategy with routine maintenance ratio $RT : RSB = 1 : 0$

Ratio 2	Full capacity number	Speed restrictions			Closures			Tamping		Stoneblowing	
		Unknown time (days)	Enforced time (days)	Enforced number	Unknown time (days)	Enforced time (days)	Enforced number	Routine	Urgent	Routine	Urgent
0 day	99.9133 %	0.000000	0.000000	0.0000 %	0.000000	0.000000	0.0000 %	0.0400 %	0.0000 %	0.0000 %	0.0000 %
1 day	99.9067 %	0.000867	0.000000	0.0000 %	0.000067	0.000000	0.0000 %	0.0800 %	0.0000 %	0.0133 %	0.0000 %
2 day	99.9000 %	0.000900	0.000000	0.0000 %	0.000067	0.000000	0.0000 %	0.1067 %	0.0000 %	0.0133 %	0.0000 %
3 day	99.8933 %	0.000933	0.000000	0.0000 %	0.000067	0.000000	0.0000 %	0.1333 %	0.0000 %	0.0200 %	0.0000 %
4 day	99.8933 %	0.000950	0.000000	0.0000 %	0.000067	0.000000	0.0000 %	0.1467 %	0.0000 %	0.0200 %	0.0000 %
5 day	99.8933 %	0.000760	0.000200	0.1000 %	0.000053	0.000013	0.0067 %	0.1867 %	0.1067 %	0.0267 %	0.0933 %
10 day	99.8800 %	0.000420	0.000587	0.1000 %	0.000040	0.000040	0.0067 %	0.3200 %	0.2467 %	0.0533 %	0.1400 %
15 day	99.8733 %	0.000342	0.000689	0.1000 %	0.000062	0.000049	0.0067 %	0.4600 %	0.2467 %	0.0600 %	0.1400 %
20 day	99.8667 %	0.000307	0.000733	0.1000 %	0.000090	0.000053	0.0067 %	0.5867 %	0.2467 %	0.0867 %	0.1400 %
25 day	99.8533 %	0.000301	0.000760	0.1000 %	0.000112	0.000056	0.0067 %	0.7467 %	0.2467 %	0.0933 %	0.1400 %
30 day	99.8400 %	0.000311	0.000778	0.1000 %	0.000127	0.000058	0.0067 %	0.9067 %	0.2467 %	0.1000 %	0.1400 %

Table 9. Predicted condition and maintenance requirements at the end of the heatwave periods following the strategy with routine maintenance schedule $F_{routine} = N(60, 15)$

Schedule 2	Full capacity number	Speed restrictions			Closures			Tamping		Stoneblowing	
		Unknown time (days)	Enforced time (days)	Enforced number	Unknown time (days)	Enforced time (days)	Enforced number	Routine	Urgent	Routine	Urgent
0 day	99.9600 %	0.000000	0.000000	0.0000 %	0.000000	0.000000	0.0000 %	0.0267 %	0.0000 %	0.0067 %	0.0000 %
1 day	99.9533 %	0.000400	0.000000	0.0000 %	0.000067	0.000000	0.0000 %	0.0533 %	0.0000 %	0.0267 %	0.0000 %
2 day	99.9533 %	0.000400	0.000000	0.0000 %	0.000067	0.000000	0.0000 %	0.0867 %	0.0000 %	0.0267 %	0.0000 %
3 day	99.9533 %	0.000400	0.000000	0.0000 %	0.000067	0.000000	0.0000 %	0.1200 %	0.0000 %	0.0533 %	0.0000 %
4 day	99.9467 %	0.000417	0.000000	0.0000 %	0.000067	0.000000	0.0000 %	0.1533 %	0.0000 %	0.0533 %	0.0000 %
5 day	99.9467 %	0.000333	0.000093	0.0467 %	0.000053	0.000013	0.0067 %	0.1800 %	0.1133 %	0.0667 %	0.1200 %
10 day	99.9067 %	0.000247	0.000280	0.0467 %	0.000040	0.000040	0.0067 %	0.3200 %	0.1600 %	0.0867 %	0.1867 %
15 day	99.9000 %	0.000298	0.000342	0.0467 %	0.000049	0.000049	0.0067 %	0.4600 %	0.1600 %	0.0933 %	0.1867 %
20 day	99.9000 %	0.000323	0.000373	0.0467 %	0.000053	0.000053	0.0067 %	0.5867 %	0.1600 %	0.1333 %	0.1867 %
25 day	99.8933 %	0.000344	0.000392	0.0467 %	0.000056	0.000056	0.0067 %	0.7133 %	0.1600 %	0.1600 %	0.1867 %
30 day	99.8867 %	0.000376	0.000402	0.0467 %	0.000060	0.000058	0.0067 %	0.8667 %	0.1600 %	0.1800 %	0.1867 %

Table 10. Predicted condition and maintenance requirements at the end of the heatwave periods following the best strategy combination

Best Strategy	Full capacity number	Speed restrictions			Closures			Tamping		Stoneblowing	
		Unknown time (days)	Enforced time (days)	Enforced number	Unknown time (days)	Enforced time (days)	Enforced number	Routine	Urgent	Routine	Urgent
0 day	99.9867 %	0.000000	0.000000	0.0000 %	0.000000	0.000000	0.0000 %	0.0467 %	0.0000 %	0.0000 %	0.0000 %
1 day	99.9867 %	0.000133	0.000000	0.0000 %	0.000000	0.000000	0.0000 %	0.0933 %	0.0000 %	0.0067 %	0.0000 %
2 day	99.9800 %	0.000167	0.000000	0.0000 %	0.000000	0.000000	0.0000 %	0.1200 %	0.0000 %	0.0067 %	0.0000 %
3 day	99.9800 %	0.000178	0.000000	0.0000 %	0.000000	0.000000	0.0000 %	0.1600 %	0.0000 %	0.0200 %	0.0000 %
4 day	99.9800 %	0.000183	0.000000	0.0000 %	0.000000	0.000000	0.0000 %	0.2000 %	0.0000 %	0.0400 %	0.0000 %
5 day	99.9800 %	0.000147	0.000040	0.0200 %	0.000000	0.000000	0.0000 %	0.2200 %	0.0667 %	0.0400 %	0.0200 %
10 day	99.9467 %	0.000153	0.000120	0.0200 %	0.000000	0.000000	0.0000 %	0.3267 %	0.0933 %	0.0533 %	0.0600 %
15 day	99.9467 %	0.000209	0.000147	0.0200 %	0.000004	0.000000	0.0000 %	0.4400 %	0.0933 %	0.0733 %	0.0600 %
20 day	99.9200 %	0.000207	0.000193	0.0533 %	0.000013	0.000013	0.0133 %	0.6000 %	0.1933 %	0.0800 %	0.1333 %
25 day	99.9067 %	0.000200	0.000261	0.0533 %	0.000011	0.000037	0.0133 %	0.7000 %	0.2000 %	0.0933 %	0.1400 %
30 day	99.9000 %	0.000218	0.000307	0.0533 %	0.000009	0.000053	0.0133 %	0.8533 %	0.2000 %	0.1267 %	0.1400 %

At steady state the track section maintenance response is as evenly distributed as the base case, so the shorter schedule time does not significantly influence the demanded maintenance volumes.

Best strategy combination

A study can be made of combining the “best” management strategies; that is, those that are individually observed to improve performance and resilience most in comparison to the base case. The combination of the best strategies would therefore seek the highest theoretical resilience that could be achieved, though with the greatest change in asset management practice and no compromise for costs and attainability. Table 11 lists the variant parameters used in this test.

Following this best combination, table 10 shows excellent availability through the opening 5 days of heatwave, starting at 99.9867 % and decreasing by only 0.0067 %. After 30 maintenance-free days 99.9 % availability remains, second only to the inspection 2 individual test (which began at 100 % availability).

The total number of *speed restrictions* and *closures* enforced is on par with the base case strategy, however the increased inspection rate is valuable in providing lower at-risk times. The simultaneous maintenance demand at the end of the heatwave periods is lower than any of the individual tests, and is strongly preferential to the easier-to-deliver tamping activity.

The best combination strategy is outperformed by the individual inspection 2 performance, for availability through the heatwave periods tested. However, the difference is small (0.0067 % at the end of 30 days), and the improvement in the simultaneous maintenance demand volume shows the optimisation that can be achieved in a multi-parameter approach.

Table 11. Best asset management strategy combination

Variable	Best combination
Poor threshold	$\sigma_{Poor} = 1.9 \text{ mm}$
Critical threshold	$\sigma_{Crit} = 2.7 \text{ mm}$
Inspection interval	$\theta = 14 \text{ days}$
Decision ratio	$RT : RSB = 1 : 0$
Routine schedule	$F_{routine} = N(60, 15)$

Example performance calculation

Finally, it is useful to relate simulation results to a real-world example. This allows rail network operators to make informed decisions about which strategy should be employed, based on the performance that may be achieved and the demand for maintenance equipment and personnel. Thus, the base case and best combination strategies are applied to an example London to Sheffield rail line. This 160-mile mainline would constitute approximately 1280 track sections assuming the standard section length throughout and ignoring alternative track layouts. This is a high quality, highly utilised rail line that requires excellent management to ensure proper working.

The base case strategy predicts only a single track section of the entire line may be in a major degradation condition up to 20 days of heatwave in table 12, and two thereafter. As a reflection of the inspection interval, this degraded section is not detected until 5 days have passed; though this is not so long, it does pose a risk to the rail users.

The simultaneous maintenance requirements remain low for a short duration heatwave, with 1 or 2 routine tamping or stoneblowing actions required across the entire rail line. At the conclusion of 30 day of hot weather, 10 routine and 2 urgent tamps, 4 routine and 2 urgent stoneblowings are accrued. The comparatively large amount of routine tamping demands may lead to run-on delays, because of equipment availability.

The best combination strategy shows an improvement over the base case, in table 13. Rounded, the expectation is for full 1280 track section availability during fair weather and short disruptions, with 1 section degraded after 10 days of heatwave or longer. The prediction for major disruption conditions remains low, though there is now a potential for enforcing a closure. This may be necessary for safety, and is testament to the increased inspection frequency, which continues through long heatwaves.

For maintenance delivery, 11 routine and 3 urgent tamps, and 2 routine and 2 urgent stoneblowing activities are demanded at the end of 30 maintenance-free days. This workload is similar to the base case result, and demonstrates that there may be capacity to implement improved management strategies with the same maintenance support as is currently used.

Conclusions

Hot weather presents serious asset management problems on an annual basis, with between £3 m and £15 m being spent on delays and cancellations per year during a modern summer; this is predicted to increase up to £28 m annually in 50 years under climate change projections¹⁶. Existing asset management tools do not currently consider the disruptive effect that hot weather can have in maintenance scheduling and delivery. A Petri net model for the geometry condition of a single rail section has been developed to include heatwave disruptions, with the capability to test a variety of asset management strategies. Comparing the track section availability and maintenance volumes gives an indication of the effectiveness of each strategy.

The initial results study compared 12 variant asset management strategies against a base case for their ability to provide a highly available rail network performance, low risk, and manageable maintenance volume. It was seen that certain parameters, such as inspection interval and degradation thresholds, could have a large effect on the performance of the simulated track section, and the amount of disruption that could be expected on the network. Notably, shorter intervals between geometry inspection events and quicker completion of routine maintenance activities

Table 12. Estimated condition and maintenance performance at the end of the heatwave periods for the base case strategy when applied to the example London to Sheffield mainline

Base Case	Number of rail sections in the London to Sheffield example						
	Full capacity	Speed restrictions	Line closures	Tamping		Stoneblowing	
				Routine	Urgent	Routine	Urgent
0 day	1279.32	0.00	0.00	0.26	0.00	0.09	0.00
1 day	1279.32	0.00	0.00	0.51	0.00	0.17	0.00
2 day	1279.32	0.00	0.00	0.85	0.00	0.43	0.00
3 day	1279.32	0.00	0.00	1.28	0.00	0.43	0.00
4 day	1279.32	0.00	0.00	1.71	0.00	0.60	0.00
5 day	1279.23	0.77	0.00	1.96	1.28	0.60	0.94
10 day	1279.15	0.77	0.00	3.58	1.96	1.19	2.47
15 day	1278.89	0.77	0.00	5.55	1.96	1.71	2.47
20 day	1278.55	0.77	0.00	7.08	1.96	2.05	2.47
25 day	1278.46	0.77	0.00	8.79	1.96	2.82	2.47
30 day	1278.12	0.77	0.00	10.24	1.96	3.50	2.47

Table 13. Estimated condition and maintenance performance at the end of the heatwave periods for the best case strategy when applied to the example London to Sheffield mainline

Best Case	Number of rail sections in the London to Sheffield example						
	Full capacity	Speed restrictions	Line closures	Tamping		Stoneblowing	
				Routine	Urgent	Routine	Urgent
0 day	1279.83	0.00	0.00	0.60	0.00	0.00	0.00
1 day	1279.83	0.00	0.00	1.19	0.00	0.09	0.00
2 day	1279.74	0.00	0.00	1.54	0.00	0.09	0.00
3 day	1279.74	0.00	0.00	2.05	0.00	0.26	0.00
4 day	1279.74	0.00	0.00	2.56	0.00	0.51	0.00
5 day	1279.74	0.26	0.00	2.82	0.85	0.51	0.26
10 day	1279.32	0.26	0.00	4.18	1.19	0.68	0.77
15 day	1279.32	0.26	0.00	5.63	1.19	0.94	0.77
20 day	1278.98	0.68	0.17	7.68	2.47	1.02	1.71
25 day	1278.81	0.68	0.17	8.96	2.56	1.19	1.79
30 day	1278.72	0.68	0.17	10.92	2.56	1.62	1.79

are variables which improve network availability when compared to the base case strategy.

The variant asset management strategies were then tested for 10 different durations of heatwave. Tables 5 through 9 present the results of using effective fair-weather strategies during the disruption of no-maintenance periods – the remaining results can be found in the supplementary data. The presented model results are limited to only considering a single heatwave event. The impact would be replicated with subsequent heatwaves, or expanded with forecast weather cycles in a longer duration simulation.

Of the 12 variations, a shorter inspection interval (14 days compared to 28 days) suggests the greatest potential resilience against disruptions. This strategy has the advantage of providing more detailed monitoring of the track condition degradation such that maintenance can be performed in a timely manner. Another advantage is reduced risk, as major degradations are more likely to be observed and traffic limits enforced. Of course, broader cost optimisation and attainability studies are suggested to frame these results in a network-wide context.

The study in table 10 assessed the best strategy asset management could hope to achieve within this hot weather disruption context. A combination of the best individual approaches could deliver greater average track geometry performance and provide resilience to long periods without maintenance. Rail network management should be motivated to deliver frequent inspections and timely maintenance schedules in order to attain a highly performing and resilient system. Finally, it is demonstrated the model can be applied to real-world situations, by relating the simulated predictions to an example London to Sheffield rail line.

The simulations complete rapidly, allowing multiple strategies to be tested in succession, and compared for effective performance. This model could contribute to the suite of asset management tools used by the rail industry, providing guidance on maintenance policy through a summer season where heatwave disruptions are expected. The presented model does rely on empirically defined parameters for many transitions; degradation rate, maintenance completion rate, and inspection interval. For further accuracy and applicability in the rail industry, these values should be tuned to suit the real-world rail network on which it is applied.

With the same format, and the correct parametrisation, the model could also be used for other asset management tasks where interventions works are restricted by no-maintenance periods. Further, as Petri net modelling has been demonstrated useful for asset management tasks, this method could be used when investigating the effects of climate change on other aspects of the rail network infrastructure; for example, washout failures of earthwork assets after local flooding events.

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References

1. Iman Soleimanmeigouni, Alireza Ahmadi, and Uday Kumar. Track geometry degradation and maintenance modelling: A review. *Proceedings of the Institution of Mechanical Engineers, Part F: Journal of Rail and Rapid Transit*, 232(1):73–102, 2018.
2. Emma Ferranti, Lee Chapman, Susan Lee, David Jaroszweski, Caroline Lowe, Steve McCulloch, and Andrew Quinn. The hottest July day on the railway network: insights and thoughts for the future. *Meteorological Applications*, 25(2):195–208, 2018.
3. Network Rail. NR/L2/TRK/3011 Continuous Welded Rail (CWR) Track. Technical report, 2012.
4. Darren Prescott and John Andrews. Modelling maintenance in railway infrastructure management. *Proceedings - Annual Reliability and Maintainability Symposium*, pages 1–6, jan 2013.
5. Bernhard Lichtberger. Track Compendium. *Hamburg, Eurailpress Tetzlaff-Hestra GmbH & Co. Publ*, pages 1–192, 2005.
6. Peter Musgrave. Track bed total route evaluation for track renewals and asset management "a Network Rail perspective". *Construction and Building Materials*, 92:2–8, sep 2015.
7. Matthew Audley and John Andrews. The effects of tamping on railway track geometry degradation. *Proceedings of the Institution of Mechanical Engineers, Part F: Journal of Rail and Rapid Transit*, 227(4):376–391, 2013.
8. P Claisse and C Calla. Rail ballast: Conclusions from a historical perspective. *Proceedings of the Institution of Civil Engineers: Transport*, 159(2):69–74, 2006.
9. Y. J. Zhang, M. Murray, and Luis Ferreira. Modelling rail track performance: An integrated approach. *Proceedings of the Institution of Civil Engineers: Transport*, 141(4):187–194, 2000.
10. Darren Prescott and John Andrews. A track ballast maintenance and inspection model for a rail network. *Proceedings of the Institution of Mechanical Engineers, Part O: Journal of Risk and Reliability*, 227(3):251–266, 2013.
11. Jianmin Zhao, A. H.C. Chan, A. B. Stirling, and K. B. Madelin. Optimizing policies of railway ballast tamping and renewal. *Transportation Research Record*, 1943(1943):50–56, 2006.
12. T. R. Sussmann, W. Ebersöhn, and E. T. Selig. Fundamental nonlinear track load-deflection behavior for condition evaluation. *Transportation Research Record*, 3(1742):61–67, 2001.
13. Emma Ferranti, Lee Chapman, Caroline Lowe, Steve McCulloch, David Jaroszweski, and Andrew Quinn. Heat-Related Failures on Southeast England's Railway Network: Insights and Implications for Heat Risk Management. *Weather, Climate, and Society*, 8(2):177–191, 2016.

14. Pavel Ryjáček and Miroslav Vokáč. Long-term monitoring of steel railway bridge interaction with continuous welded rail. *Journal of Constructional Steel Research*, 99:176–186, 2014.
15. Erika J. Palin, Hazel E. Thornton, Camilla T. Mathison, Rachel E. McCarthy, Robin T. Clark, and John Dora. Future projections of temperature-related climate change impacts on the railway network of Great Britain. *Climatic Change*, 120(1-2):71–93, sep 2013.
16. K Dobney, C. J. Baker, A. D. Quinn, and L. Chapman. Quantifying the effects of high summer temperatures due to climate change on buckling and rail related delays in south-east United Kingdom. *Meteorological Applications*, 16(2):245–251, jun 2009.
17. K Dobney, C J Baker, L Chapman, and A D Quinn. The future cost to the United Kingdom’s railway network of heat-related delays and buckles caused by the predicted increase in high summer temperatures owing to climate change. *Proceedings of the Institution of Mechanical Engineers, Part F: Journal of Rail and Rapid Transit*, 224(1):25–34, 2010.
18. Minh N. Nguyen, Xiaoming Wang, and Chi Hsiang Wang. A reliability assessment of railway track buckling during an extreme heatwave. *Proceedings of the Institution of Mechanical Engineers, Part F: Journal of Rail and Rapid Transit*, 226(5):513–517, 2012.
19. Mohammad Yousefikia, Sara Moridpour, Sujeeva Setunge, and Ehsan Mazloumi. Modeling Degradation of Tracks for Maintenance Planning on a Tram Line. *Journal of Traffic and Logistics Engineering*, 2(2):86–91, 2014.
20. C. Meier-Hirmer, G. Riboulet, F. Sourget, and M. Roussignol. Maintenance optimization for a system with a gamma deterioration process and intervention delay: Application to track maintenance. *Proceedings of the Institution of Mechanical Engineers, Part O: Journal of Risk and Reliability*, 223(3):189–198, 2009.
21. Sophie Mercier, Carolina Meier-Hirmer, and Michel Roussignol. Bivariate Gamma wear processes for track geometry modelling, with application to intervention scheduling. *Structure and Infrastructure Engineering*, 8(4):357–366, 2012.
22. Mengyi Zhu, Xiaohui Cheng, Lixin Miao, Xinya Sun, and Shuai Wang. Advanced stochastic modeling of railway track irregularities. *Advances in Mechanical Engineering*, 2013, 2013.
23. Cecília Vale and Simões M. Lurdes. Stochastic model for the geometrical rail track degradation process in the Portuguese railway Northern Line. *Reliability Engineering and System Safety*, 116:91–98, 2013.
24. Cecília Vale and Isabel M. Ribeiro. Railway condition-based maintenance model with stochastic deterioration. *Journal of Civil Engineering and Management*, 20(5):686–692, 2014.
25. Y. Shafahi and R. Hakhamaneshi. Application of a maintenance management model for Iranian Railways based on the Markov chain and probabilistic dynamic programming. *Scientia Iranica*, 16(1 A):87–97, 2009.
26. Wenfei Bai, Rengkui Liu, Ru An, Futian Wang, and Quanxin Sun. Renewal Management Framework for Urban Rail Transit Assets. *Transport*, 34(1):9–18, 2019.
27. Claudia Fecarotti and John Andrews. A mathematical programming approach to railway network asset management. *Safety and Reliability – Safe Societies in a Changing World*, pages 839–847, 2018.
28. John Andrews. A modelling approach to railway track asset management. *Proceedings of the Institution of Mechanical Engineers, Part F: Journal of Rail and Rapid Transit*, 227(1):56–73, jan 2013.
29. Matthew Audley and John Andrews. A Petri-Net Modelling Approach to Rail Track Geometry Maintenance and Inspection. In *Proceedings of the 20th Advances in Risk and Reliability Technology Symposium*, pages 230–243, 2013.
30. Jack Litherland and John Andrews. A Petri Net Methodology for Modelling the Maintenance of Railway Route Sections. *Proceedings of the 29th European Safety and Reliability Conference*, 2019.
31. M. Sol-Sánchez, F Moreno-Navarro, and M C Rubio-Gámez. Analysis of ballast tamping and stone-blowing processes on railway track behaviour: The influence of using USPs. *Geotechnique*, 66(6):481–489, 2016.
32. Mark J. Koetse and Piet Rietveld. The impact of climate change and weather on transport: An overview of empirical findings. *Transportation Research Part D: Transport and Environment*, 14(3):205–221, 2009.
33. Network Rail. Track treatment fleet - Network Rail.