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RESEARCH ARTICLE

The impact of high temperatures and extreme heat to delays on the London Underground rail network: An empirical study

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Abstract

Rail infrastructure is vulnerable to extreme weather events, resulting in damage and delays to networks. The impact of heat is a major concern for the London Underground (LU) by Transport for London (TfL) both now and in future, but existing studies are limited to passenger comfort on the deep tube and do not focus on infrastructure or the vast majority of the network, which is in fact above ground. For the first time, the present empirical study examines quantitatively the statistical relationship between LU delays (by synthesizing 2011–2016 industry data) with air temperature data (from Met Office archives). A range of testing shows strong statistical relationships between most delay variables and high temperatures, though not causality. Relationships were found between high temperatures and delays associated with different asset classes on different LU lines. Track-related delays, often the focus of high-temperature research (i.e. track buckling), show a relationship, although this is small relative to delays caused by other assets. Using UK Climate Projections 2009 (UKCP09) and assuming a similar future performance indicates that the share of annual delays owed to temperatures > 24°C may increase in frequency and length, depending on the emissions scenario. Recommendations include extending the analysis to the LU asset scale and considering the local environment to understand failure causality in order to mitigate future heat risk. A review of how TfL and other infrastructure operators capture delays for future analysis is necessary to facilitate climate resilience benchmarking between networks.

KEYWORDS

climate change, London, railway, underground

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1 | INTRODUCTION

Transport networks are critical for societal function, supporting the movement of commuters, goods and services. They contribute to the global economy, forming 5.0% and 8.9% of gross domestic product (GDP) in the United States and Europe, respectively (European Commission, 2016; USDT, 2016). Extreme weather events such as floods, storms and extreme heat impact transport services, causing delay and disruption for passengers and freight users. Accelerated anthropogenic greenhouse gas emissions, accountable for recent mean global temperature increases, are anticipated to affect the intensity and frequency of extreme weather events (IPCC, 2013). Therefore, there is an increasing need for the transport sector to understand climate adaptation opportunities.

High temperatures affect rail network performance, often on a regional scale, in comparison with flooding and rainfall events, which are typically more localized (WMO & WHO, 2015). The response of railway assets to high temperature is complex for many reasons. First, railway infrastructure incorporates a wide range of asset types, including track, signalling and power supply, and each asset type has a different operative threshold for heat. Second, the exposure of any particular asset to heat depends on local environmental conditions, in particular the amount of shading (Chapman *et al.*, 2006), which may well be unknown at the point of data analysis. Third, heat can impact rail assets in different ways. It can cause direct asset failure. For example, thermal expansion of track in hot weather can cause rail buckling and train derailment (Dobney *et al.*, 2009); and excessive heat stress on electricity provision networks can reduce asset life expectancy (Chapman *et al.*, 2013).

The first few hot days of the year are also associated with increased levels of non-specific asset failures (“failure-harvesting”; Ferranti *et al.*, 2016), as are days with a diurnal temperature range $> 12^{\circ}\text{C}$ (Network Rail, 2015). Heat also leads to “accelerated ageing” of an asset, reducing the asset’s lifespan or increasing the associated maintenance costs. The combination of these factors makes attributing asset failure to high temperatures problematic, not least because operator databases are not designed to record this type of information, and can also be subject to data-recording errors. As such, quantifying the impact of high temperatures on railway performance is difficult, and makes predicting and planning for high-temperature events problematic for the operator. For example, the environmental conditions and amount of shading is unknown for many assets and results in its lack of focus in the public domain (Ferranti *et al.*, 2017).

The recurrence of extreme high temperatures in the UK has increased in recent decades, with many record-

breaking maximum temperatures reached. According to the UK Climate Projections 2009 (UKCP09) medium-emissions scenario, the prospective summer “heat wave” season will increase in length moving into the 21st century, occurring annually in the UK by the 2050s, especially in the southeast of England (Sanderson and Ford, 2017). This will be exacerbated in cities because of the urban heat island effect (Oke, 1973; Terjung and Louie, 1973). London is a particular risk area regarding the performance of its transport infrastructure given that it can experience $8\text{--}10^{\circ}\text{C}$ spatial variability in summer temperatures (Holderness *et al.*, 2013). Railway infrastructure often has a long lifespan, and current and future planned assets will be expected to function in this projected future climate. Therefore, it is imperative that railway operators plan and adapt for climate change (Quinn *et al.*, 2018), or else risk facing a greater cost of climate change impacts to their assets with a reactive approach (Chinowsky *et al.*, 2019). Heat waves are short in duration and can reach maximum intensity very quickly (PHE, 2015). Hence, operators must plan in advance to be ready for heat risks.

1.1 | The London Underground (LU) network

LU is the oldest and one of the largest underground train networks in the world, currently managed by Transport for London (TfL). It comprises 402 km of track and 270 stations across 11 lines (TfL, 2017a), with 37% of its track in deep-mined tube tunnels (Jenkins *et al.*, 2014), carrying 1.37 billion passengers annually (TfL, 2017b). Network disruption, for example, because of extreme weather, is costly to both London and the UK-wide economy.

LU measures delays in terms of lost customer hours (LCH): “the total extra journey time, measured in hours, experienced by Underground customers as a result of all service disruptions with durations of two minutes or more” (TfL, 2017c). LCH is a financial metric, calculated by considering the number of customers affected, time of day and day of week, and adjusting the “cost” of a customer’s time (hr) accordingly. “Weather” is a factor incorporated into LCH reporting, though there is no explicit procedure for recording the type of weather (e.g. heat or rain) and the type of delay it has caused (e.g. rail buckle). Those delays that can obviously be attributed to weather, such as track flooding following heavy rain, tend to be included, but there is no uniformity in the recording process. This is particularly problematic when considering heat because it impacts assets in many ways as outlined. As LCH is a measure unique

to TfL, it cannot be compared with other methods of operational performance from a benchmarking perspective by other researchers and rail networks.

Although there has been significant research on the impacts of heat on rail performance (e.g. Dobney *et al.*, 2009; Baker *et al.*, 2010; Jenkins *et al.*, 2014; Doll *et al.*, 2014a, 2014b; Jaroszweski *et al.*, 2015; Ferranti *et al.*, 2016; Roca *et al.*, 2016; Brazil *et al.*, 2017; Fu and Easton, 2018), research of the temperature impacts on LU has generally focused on the impacts to passenger comfort (e.g. Jenkins *et al.*, 2014), especially across the deep tube section of the network where the temperatures experienced tend to be highest. Here, tunnel temperatures are amplified through heat generation because of train braking mechanisms (Ampofo *et al.*, 2004), exacerbated by geology as the efficiency of London clay as a heat sink has reduced over time (Ampofo *et al.*, 2004; Botelle *et al.*, 2010). Indeed, climate projection analyses observe LU network temperatures below ground likely to reach 40°C in parts on the hottest summer days (Arkell and Darch, 2006). This leads to near-complete passenger dissatisfaction with thermal environments on trains (Jenkins *et al.*, 2014) where train cooling alone will not satisfy the extent of the cooling required on the LU network by the 2050s to maintain operational passenger comfort.

TfL-led risk assessments conclude that impacts to the LU network infrastructure from extreme heat are extremely likely to happen, with consequent moderate impacts to the network. Particular risks projected include the overheating of trains, platforms and stations, as well as the failure of communication, signalling and power assets (TfL, 2011, 2013a, 2015). However, these impacts are poorly quantified, and there is a need for a robust statistical analysis of the current impact of heat on under- and over-ground assets in order to inform heat-risk mitigation and long-term planning for climate change.

2 | METHODOLOGY

2.1 | Delay data

The database used for the analysis (Nominally Accumulated Customer Hours System) captures delays for the purpose of calculating the LCH, covering: delays in service; trains out of service; line closures; speed restrictions; signal failures; late start-ups; station closures; and lifts and escalators out of service. The incidents' impacts are calculated through the estimated increased passenger journey time, translated to disbenefit by multiplying by the current value of time (TfL, 2013b). Aggregated

summary results are published periodically on the TfL website (TfL, 2018a), approximately every four weeks.

The LU delay data provided by TfL for this analysis covered the period between January 1, 2011, and December 31, 2016. It contained 192,541 individual delay records, detailing time, date, train operating line, cause of delay and length of delay (min), including a free-text field to capture qualitative information. Each record within the data set described a delay, logged in real time by LU staff at a station, depot, shed or siding.

For the purpose of aggregated analysis, columns were added to the existing database to record additional information for each delay. This included combined "initial delay" minutes and "subsequent duration" (which are two separate data columns in the original data set); quarter of the year; and station location, whether above or below ground (TfL, 2012). Following discussions with TfL, the recorded location of the delay at the station level was not included in the analysis because of suspected inconsistencies in record-keeping. In some cases, a delay was not recorded until the train reached the end of its route or arrived at the depot. Additionally, as the recording process is manual, it cannot be guaranteed that every single delay that meets the criteria for capture is obtained. The nature of the LU network as a high-frequency service means there is no schedule with which to compare delays, thus the extent of recorded delays may not be fully represented within the database.

The research represents the first assessment of the impact of temperature across the whole LU network. Although this analysis is focused on high temperatures, it was not restricted explicitly to hot days, or indeed the summer season, since heat-related impacts occur across a range of temperatures and asset operational thresholds are not always aligned to design standards (Network Rail, 2015). As rail assets need to withstand all seasons, the full temperature range is shown in this initial assessment and the results.

In order to select only those delays where temperature could be a potential cause, the data set was reviewed by "cause category", as recorded by the LU staff member recording the incident. As the paper is focused on asset failure relationships exclusively, all human-induced cause categories, such as passenger/staff illness, personal accidents/injury and criminal activity, were removed, leaving only those delays associated with infrastructure. These categories were:

- Asset performance (AP) power: Energy supplied internally through TfL assets.
- Connect/prestige: LU passenger ticketing/fare collection system and infrastructure.

- Distribution network operator (DNO) power: Energy supplied by the UK National Grid's infrastructure.
- Fleet: Physical train infrastructure and components; rolling stock.
- National Rail: The UK's wider rail infrastructure operated by Network Rail that subsequently impacts LU.
- Station infrastructure: Physical operational components within the boundary of a train station.
- Track and civils: The track on which the trains operate across London and reside when not in service at depots. Civils comprises the structural support for these tracks, such as bridges and deep-tube tunnels (TfL, 2016).

The final data set prepared for analysis obtained from the LU database comprised 85,509 delay incidents, equating to 44% of the full data set delays between 2011 and 2016.

2.2 | Meteorological data

Meteorological data for the same period (January 1, 2011–December 31, 2016) were taken from the MIDAS land surface data set available from the Centre for Environmental Data Analysis (CEDA) (2017). Geographical information system software was used to select those weather stations from the MIDAS data set that were located within 10 km of the LU network, as this encompassed almost the entirety of the network. This resulted in 10 weather stations for use.

For each weather station, several temperature variables were available, including maximum air, ground and grass temperatures measured twice daily at 0900 and 2100 hours. This was the only detailed temperature data set available for this area and time period in accordance with the delay data. As a result, the absolute daily maximum temperatures *per day* were not reflected (i.e. early/mid-afternoon). Previous studies investigating the relationship between high temperatures and railways used air temperature data, such as the absolute daily maximum recorded temperature (Dobney *et al.*, 2009, 2010; Jenkins *et al.*, 2014) or the mean of maximum daily temperature across a subset of weather stations (Ferranti *et al.*, 2016). Initial checks of the meteorological data also showed air temperature to have the most complete series compared with those available for ground or grass measurements for the selected weather stations. The means of the two recorded daily temperature *per day* (T_{max}) were calculated against every single delay record in order to provide a single daily temperature value *per* weather station. For example, July 12, 2015, for Heathrow Airport was observed to reach 36.7°C (Kendon *et al.*, 2016), though the calculated T_{max} was 31.9°C.

The lowest Euclidean distance between every LU station and weather station was calculated in order to synthesize a single T_{max} variable to every delay in the LU database. Where a weather station failed to record data, the next nearest weather from those selected was used, as five weather stations ceased to record temperatures at varying points through the duration of the study period. This was adjusted manually referencing 5 and 10 km distance buffers around each weather station to gauge the next closest weather station. A total of 1,072 delay incidents were removed from the LU database between December 12–31, 2011, and December 23–31, 2012, as no temperature data were recorded by any weather station.

2.3 | Climate projections

The UKCP09 climate projections were used in order to understand how the impact of temperatures may impact LU delays in future. Projections for low (B1), medium (A1B) and high (A1FI) emissions scenarios were obtained from the UKCP09 (accessed in 2018). The values, produced by the UK Meteorological Office Hadley Centre models HadCM3, HadRM3 and HadSM3 (Murphy *et al.*, 2007), were divided into monthly sets of 107 values and averaged to provide a table of mean change in °C *per* emissions scenario, *per* time period, *per* month. Baseline temperature statistics were also compiled from the LU data set in order to compare how the number of days annually exceeding certain temperature thresholds could change over time, by emissions scenario. Temperature thresholds selected were the number of days that the $T_{\text{max}} > 24$ and $> 27^\circ\text{C}$, as UK rail infrastructure operators take precautionary measures on their networks from 24°C (PHE, 2015), and 27°C is the recognized point at which assets such as track begin to buckle (Dobney *et al.*, 2009).

2.4 | Derived metrics

In order to understand the impact of high temperatures, and following discussions with analysts based at TfL, four variables (year, LU line, cause category and location) were cross-analysed against five delay metrics (Table 1). Although low temperatures can have an impact on delays and they are not the focus of the paper, low temperature metrics were not considered.

A range of delay metrics was tested as performance is not measured in the same way across infrastructure operators and researchers, for example: frequency or number of delays or incidents over a given period (Ferranti *et al.*, 2016; Fu and Easton, 2018); delay minutes deriving from the length of the delay (min) to the schedule

TABLE 1 Description of each metric tested

Metric	Description
$F\bar{C}_{\text{daily}}$	Mean daily frequency of delays
$L\bar{C}_{\text{daily}}$	Mean daily length of delays (min)
$H\bar{C}_{\text{daily}}$	Mean daily lost customer hours (LCH)
$L\bar{C}_{\text{delay}}$	Mean delay length (min)
$H\bar{C}_{\text{delay}}$	Mean delay LCH

(Dobney *et al.*, 2009; Jaroszowski *et al.*, 2015; Ferranti *et al.*, 2016; Roca *et al.*, 2016; Fu and Easton, 2018); mean journey or subsequent delay length (Brazil *et al.*, 2017); overall economic/damage costs to a given network or asset over a period of time (Baker *et al.*, 2010; Doll *et al.*, 2014a, 2014b); and customer dissatisfaction (Jenkins *et al.*, 2014). The five metrics selected were all obtainable directly from the LU database content, and as such enabled direct comparison between their relationships with temperature in order to identify what is affected to a greater extent by temperature change.

2.5 | Analytical approach

Analysis was undertaken in three steps. First, regression was used to test statistically the significance of each variable and delay metric to the $T\bar{C}_{\text{max}}$. Preliminary testing of data indicated that trends were nonlinear, often parabolic (Network Rail, 2015). Regression, therefore, comprised three co-efficients to satisfy the quadratic equation $y = b_0 + b_1x + b_2x^2$, where x is the $T\bar{C}_{\text{max}}$ to find y , where y is the delay metric. Variables and delay metrics were also rationalized based on the strength of their correlation co-efficients ($r^2 \geq 0.5$) and statistical significance ($p \leq 0.05$). The hypothesis tested for all regression undertaken is whether delay metrics increase as temperature diverges from the mean London annual temperature of 15°C (though the focus here is on the higher temperature range). The strongest relationships were then highlighted and investigated in more detail with further statistical testing. Second, the delay metrics from periods of extreme heat within the data set were reviewed. These periods were defined as days where the $T\bar{C}_{\text{max}}$ was significantly higher than the respective monthly $T\bar{C}_{\text{max}}$. The delay metrics and variables of extreme heat periods were compared with delay metric and variable monthly means in order to identify change in the delay distribution. Where necessary, the individual delay incident was reviewed for further details on the cause of the delay, and whether the temperature was logged as part of the

TABLE 2 Regression co-efficients of all prepared data for analysis by change in each delay metric *per* 1°C increment in the $T\bar{C}_{\text{max}}$

	r^2	b_0	b_1	b_2
$F\bar{C}_{\text{daily}}$	0.91**	54.59	−3.02	0.12
$L\bar{C}_{\text{daily}}$	0.69**	1,284.10	−87.47	3.16
$H\bar{C}_{\text{daily}}$	0.79**	40,661.00	−2,298.60	91.65
$L\bar{C}_{\text{delay}}$	0.19*	23.29	−0.42	0.01
$H\bar{C}_{\text{delay}}$	0.06	743.71	−1.52	0.11

Note: * $p \leq 0.05$; ** $p \leq 0.01$.

incident. Finally, climate projection statistics were reported as outlined in Section 2.3.

3 | RESULTS

3.1 | Aggregate results and key findings

Each delay metric was compared with the change in the $T\bar{C}_{\text{max}}$, reporting correlation and regression co-efficients as shown in Table 2. The mean daily metrics had a strong parabolic relationship with change compared with temperature. However, this was not the case for mean individual delay metrics. Despite the $H\bar{C}_{\text{daily}}$'s high correlation co-efficient, the same cannot be said for the $H\bar{C}_{\text{delay}}$, which has a weak parabolic relationship and no statistical significance to change in the $T\bar{C}_{\text{max}}$. The LCH is therefore limited as a measurable metric in the context of temperature change. All mean daily metrics report greater values at the highest temperatures as opposed to the lowest temperatures.

All delay metrics and variables selected for analysis were distributed disproportionately amongst the prepared data, suggesting that some parts of the LU network are more susceptible to delays than others. Across the entire prepared data analysed, there was a general improvement in annual total number of delays and LCH over time (from 19% to 15% and from 16% to 19% between 2011 and 2016, respectively). However, delay length increased slightly (from 16% to 19%).

As the $F\bar{C}_{\text{daily}}$ indicates the strongest parabolic relationship, Figure 1 highlights two different ways this breaks down by variables (LU line and general delay location). The Central line has the greatest overall share of the $F\bar{C}_{\text{daily}}$ (Figure 1a) and is double that of any other LU line's $F\bar{C}_{\text{daily}}$ when the $T\bar{C}_{\text{max}} > 30^\circ\text{C}$.

LU-wide, the $F\bar{C}_{\text{daily}}$ is predominantly greater below ground; however, the $F\bar{C}_{\text{daily}}$ above ground increases at a greater rate from around a $T\bar{C}_{\text{max}} > 20^\circ\text{C}$, reporting more

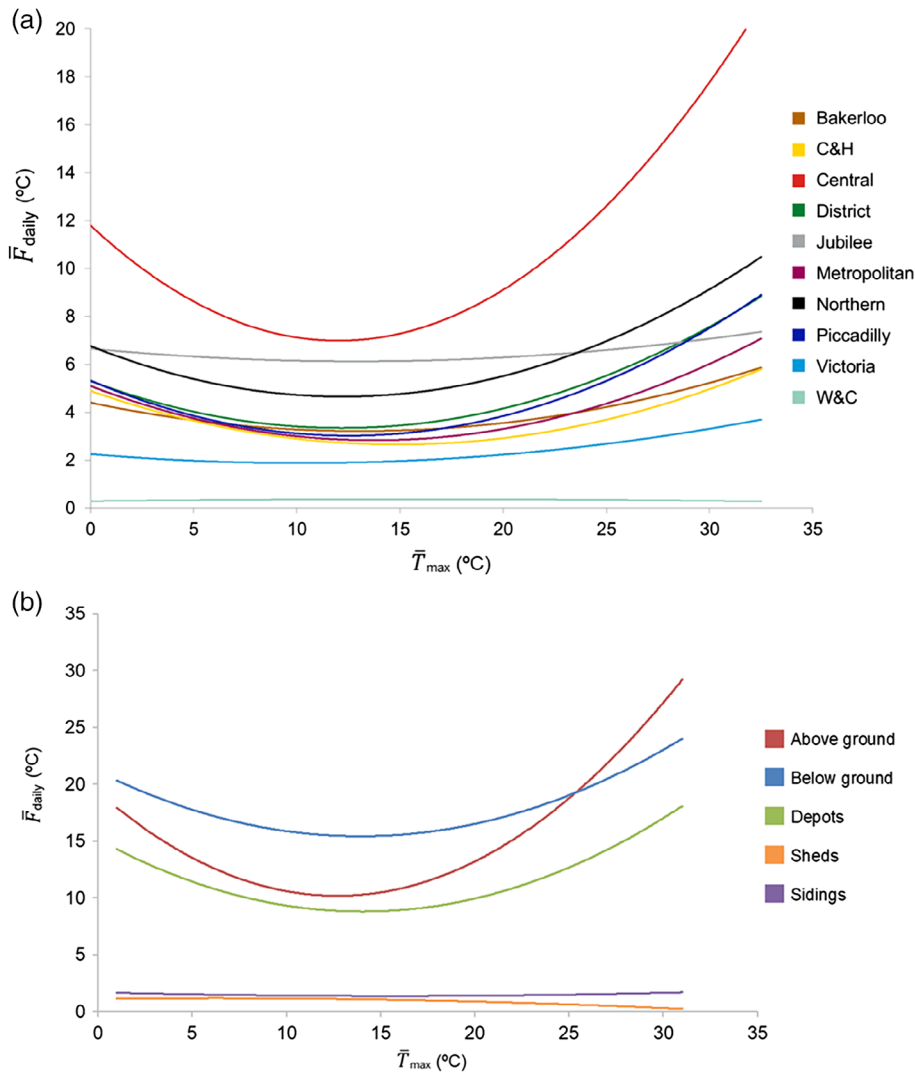


FIGURE 1 Trend lines by change in the F_{c_daily} per 1°C increment in the T_{c_max} by (a) London Underground line and (b) location. C&H, Circle & Hammersmith lines; W&C, Waterloo & City line

	r^2	b_0	b_1	b_2
Asset performance (AP) power	0.25*	0.41	-0.04	0.00
Connect/prestige	0.10	0.28	-0.01	0.00
Distribution network operator (DNO) power	0.40**	0.47	-0.07	0.00
Fleet	0.86**	23.69	-1.33	0.05
National Rail	0.38**	0.65	-0.03	0.00
Signals	0.75**	9.50	-0.56	0.02
Station infrastructure	0.77**	15.58	-0.75	0.03
Track and civils	0.61**	4.27	-0.31	0.01

TABLE 3 Correlation and regression co-efficients for all data by change in the F_{c_daily} per 1°C increment in the T_{c_max} per London Underground cause category

delays above than below ground when the $T_{c_max} > 24^{\circ}\text{C}$ (Figure 1b). These figures also show an increase in delays at low temperatures on the Central line (Figure 1a) and above ground (Figure 1b).

The F_{c_daily} is also broken down by cause category (Table 3) to identify the asset categories most susceptible to delays. As the LU lines and network has developed

over varying timescales, asset age will also vary, so high correlation co-efficients may indicate pre-existing vulnerabilities. Here, the fleet-related F_{c_daily} reports the strongest parabolic relationship to the T_{c_max} , followed by station infrastructure, signals, and track and civils. Each of these cause categories was further broken down by LU line and the following highlights were drawn.

3.1.1 | The Central line is the principal driver of the fleet-related $F\bar{C}_{\text{daily}}$ at every $T\bar{C}_{\text{max}}$

Within the Central line, a high proportion of its $F\bar{C}_{\text{daily}}$ is because of asset failures of its fleet, particularly when the $T\bar{C}_{\text{max}}$ is high. Four fleet-related assets drive this trend (automatic train control; auxiliary system; fault reporting equipment; and heating and ventilation). Delays due to heating and ventilation have the greatest correlation coefficient ($r^2 = 0.77$). On days when the $T\bar{C}_{\text{max}} > 28^\circ\text{C}$, there is an average of two delays because of heating and ventilation failures, each lasting on average 13 min. Therefore, the expected $L\bar{C}_{\text{daily}}$ impact to Central line commuters on such a day is 26 min.

3.1.2 | A combination of LU lines contributes to the overall station infrastructure $F\bar{C}_{\text{daily}}$

These LU lines are the Circle & Hammersmith (C&H), Metropolitan, Northern, and Piccadilly, all reporting $r^2 \geq 0.5$. The station infrastructure $F\bar{C}_{\text{daily}}$ increases are predominantly because of component failures on escalators and lifts at stations on the LU lines. Escalator component failures occur more frequently than lift component failures, and increase at a greater rate as the $T\bar{C}_{\text{max}}$ increases. The average number of delays with lift and escalator failures when the $T\bar{C}_{\text{max}} > 24^\circ\text{C}$ is between three and five. However, the average delay length of these is < 1 min, so the delay impact to a commuter on a hot day may be no more than 5 min.

3.1.3 | The District line drives the signal-related $F\bar{C}_{\text{daily}}$, particularly once the $T\bar{C}_{\text{max}} > 15^\circ\text{C}$

Within District line signalling assets, only one asset type (links) is notably impacted by change in the $T\bar{C}_{\text{max}}$ ($r^2 = 0.55$). This is related to issues such as blown fuses and cable faults to signalling equipment when in operation. The $F\bar{C}_{\text{daily}}$ is also greatest when the $T\bar{C}_{\text{max}}$ is high, although this type of delay occurs on average less than once *per* day. Other asset types are statistically significant, though correlation co-efficients are low. However, as there are more asset types within signals than fleet or station infrastructure, there is a likely compounding influence on the overall signals cause category. A links-related delay is an average of 93 min, which, though infrequent, has the potential to cause significant delay to a commuter on a hot day.

3.2 | Periods of extreme heat

Three periods of extreme heat of varying lengths were identified in the data set: July 3–23, 2013; July 1, 2015; and 12–15 September, 2016. Figure 2 shows that during the July 2013 heat event, track and civils delays were higher than the July average. Several track speed restrictions (TSRs) were enforced (94 of 153 track and civils delays recorded), and track temperatures were recorded on the LU database at some sites at $> 42^\circ\text{C}$. A total of 64 of these delays were documented as being enforced directly because of heat-related conditions, exceeding critical rail temperatures. The remainder of the TSR-related delays were documented as rail defects (apart from one, which was a tree-related track issue), but heat-related conditions were not mentioned and therefore cannot be assumed to be related.

During the single hot day of July 2015, the $L\bar{C}_{\text{daily}}$ was double the July mean, predominantly caused by a range of signals and fleet incidents on the District and Piccadilly lines. Delays caused by DNO power incidents on July 1, 2015 (Figure 2), were greater than the July mean because of two power cuts that closed one LU station for most of the day. During September 12–15, 2016, the $L\bar{C}_{\text{daily}}$ for this period was double the September mean. There was a greater number of fleet-related delays (Figure 2) because of component failures across many different fleet assets on the Central Line (40 of 100 fleet delays recorded).

3.3 | Climate projections

During the analysis period for the study (January 1, 2011–December 31, 2016) there were nine days where $24 < T\bar{C}_{\text{max}} < 27^\circ\text{C}$ and three days where the $T\bar{C}_{\text{max}} > 27^\circ\text{C}$. Table 4(a) shows that the number of days likely to exceed these temperatures according to the UKCP09 emissions scenarios will increase, extending the summer season. For example, in a low-emissions scenario, the $T\bar{C}_{\text{max}} > 24^\circ\text{C}$ only occurs between June and mid-August; however, under a medium-emissions scenario, this extends into early September by the 2080s. This is also similar under the high-emissions scenario, though by the 2080s the $T\bar{C}_{\text{max}} > 27^\circ\text{C}$ occurs regularly between mid-July and mid-August. Consequently, without adaptation or asset renewal, delay projections will increase under all scenarios (Table 4, b, c). Current analysis reveals that 3.1% of annual delays (accounting for 3.0% of the total delay length) take place when $24 < T\bar{C}_{\text{max}} < 27^\circ\text{C}$. When the $T\bar{C}_{\text{max}} > 27^\circ\text{C}$, this is an additional 1.3% for both the number and length of delays. Assuming similar asset performance and relationships to temperature in future, the annual proportion of delays that take place when the $T\bar{C}_{\text{max}} > 24^\circ\text{C}$ in the 2080s

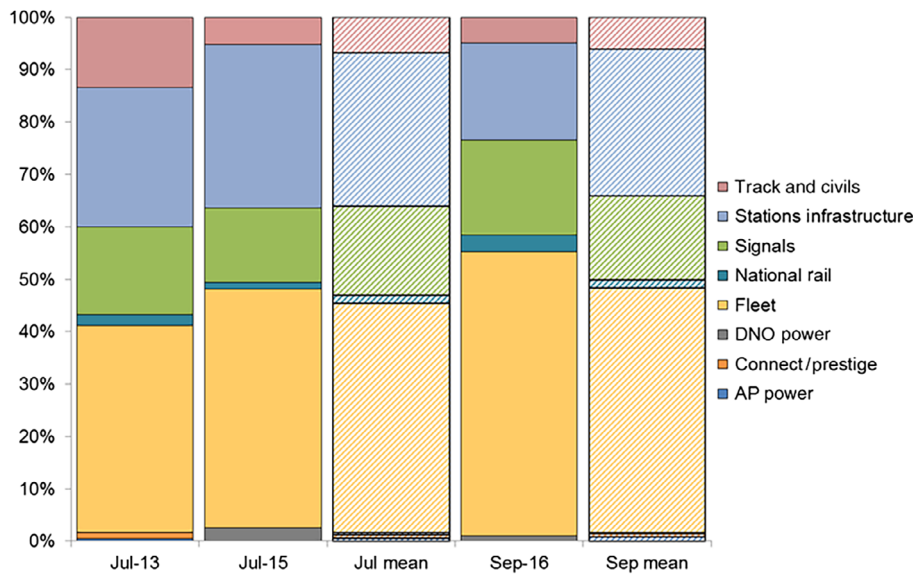


FIGURE 2 Comparison of the relative proportion of the total number of delays between high-temperature periods (solid fill) and their monthly means (diagonal fill) by cause category. AP: asset performance; DNO: distribution network operator

			Low (B1)	Med (A1B)	High (A1FI)
(a)	$24 < T_{\text{max}} < 27^{\circ}\text{C}$	2030s	14	33	41
		2050s	16	36	57
		2080s	19	49	50
	$T_{\text{max}} > 27^{\circ}\text{C}$	2030s	0	0	0
		2050s	0	0	6
		2080s	0	0	29
(b)	$24 < T_{\text{max}} < 27^{\circ}\text{C}$	2030s	5.0%	5.7%	6.7%
		2050s	11.7%	12.8%	17.4%
		2080s	14.6%	20.3%	17.4%
	$T_{\text{max}} > 27^{\circ}\text{C}$	2030s	0.0%	0.0%	0.0%
		2050s	0.0%	0.0%	0.0%
		2080s	0.0%	2.4%	11.4%
(c)	$24 < T_{\text{max}} < 27^{\circ}\text{C}$	2030s	5.2%	5.9%	7.0%
		2050s	12.2%	13.4%	18.2%
		2080s	15.3%	21.2%	18.1%
	$T_{\text{max}} > 27^{\circ}\text{C}$	2030s	0.0%	0.0%	0.0%
		2050s	0.0%	0.0%	0.0%
		2080s	0.0%	2.5%	12.2%

TABLE 4 (a) Number of days annually, (b) relative proportion of the total number of annual delays and (c) relative proportion of the total length of annual delays (min) estimated to exceed the 24 and 27°C thresholds in the T_{max} in a typical year according to UK Climate Projections 2009 (UKCP09) emissions scenarios

under a high-emissions scenario could increase to 28.8%. In addition to an increase in delays at high temperatures, there may be a corresponding reduction in delays at low temperatures, for there may be fewer cold days.

4 | DISCUSSION

The paper highlights how different delay metrics are affected by high temperatures on the LU network. First, the strongest relationship lies between the T_{max} and

$F\bar{C}_{\text{daily}}$, as well as a relatively strong relationship between the T_{max} and $L\bar{C}_{\text{daily}}$. Although the $H\bar{C}_{\text{daily}}$ also indicated a strong relationship, there are external factors that are demonstrated by no statistical significance between the T_{max} and $H\bar{C}_{\text{daily}}$. Second, the distribution of delays by tested variables is uneven. The strongest relationships lie across assets on the Central line's fleet, signals on the District line, and above compared with below ground as the T_{max} increases. Third, the $F\bar{C}_{\text{daily}}$ and $L\bar{C}_{\text{daily}}$ have the potential to double compared with their monthly means during extreme heat events under current operative

conditions. Finally, delays caused by high temperatures are likely to increase as a relative proportion to the total annual delays under all climate change projection scenarios.

4.1 | Implications for TfL

The paper has produced the first results of their kind for the LU network. Consequently, TfL was able to take first steps in future heat mitigation with quantitative evidence, and some of these results have been presented to stakeholders in the UK government. The $F\bar{C}_{\text{daily}}$ is particularly affected when the $T\bar{C}_{\text{max}}$ is high. Central line trains are around 25 years old, which is within the acceptable lifespan (30–50 years) for rolling stock (TfL, 2017d). The identified heating and ventilation asset failures are linked to passenger comfort and, as such, often lead to service withdrawal. Other rail networks have experienced similar failures, such as in Melbourne's (Australia) summer in 2009 (McEvoy *et al.*, 2012), but climatic and asset conditions are not comparable with LU. Heating and ventilation assets, therefore, require a greater level of investigation in order to identify the cause of failure in such conditions as it cannot be assumed from other case studies.

TfL has already installed several different types of heat-mitigation measures on the LU network. These include new air-conditioned rolling stock across some LU lines (District, Metropolitan, and C&H) and increased ventilation shaft capacity on selected LU lines' station platforms. However, it is important to note that land availability is highly restricted within London and it limits the extent of installing measures such as these. Additional trackside management takes place in the form of "heat duties" by staff who inspect track conditions and enforce TSRs to mitigate derailment risk.

However, these measures do not yet consider all the addressed hazards in terms of the relationships identified in Section 3.1. For example, there are currently no measures to address the signalling failures because of high temperatures and the long delays they cause (albeit fairly infrequently). The signalling equipment on the District line is reported as "legacy" equipment, and is degrading due to its age (TfL, 2016), but it is not clear whether this degradation has been accelerated by weather-related impacts. Information and communication technology-based assets' risk of obsolescence and overall shorter lifespan than assets such as rolling stock, track and bridges highlights the growing importance of integrating weather exposure into an asset's life cycle cost-benefit analysis to improve its resilience. Where current signalling assets are already vulnerable to failure under high

temperature conditions, it is imperative that asset renewal processes take into account the impact of current weather and longer time climatic change.

Furthermore, the paper highlights that heat-related failures on non-track assets can be the greatest contributors to delay metrics: track-related delays are a small proportion of overall delays during high temperatures on the LU network. LU track is continually welded and designed to be stress neutral at 27°C, and no track buckling incidents are recorded in the LU database. TfL is thus confident in its track resilience under extreme high temperatures (TfL, 2018b), and as track conditions influence their buckling thresholds (Dobney *et al.*, 2009), this also infers that LU track is in good condition. Nevertheless, high temperatures tend to be combined with drier conditions. Moisture-sensitive clays, the principal construct of London geology, can contract, leading to track geometry distortion (Doherty *et al.*, 2012; Pritchard *et al.*, 2014). This warrants further investigation into future LU track hazards and their risk beyond buckling.

4.2 | Implications for the rail industry and infrastructure operators

The paper recognizes that there are clear trends and relationships between delays and high temperatures. However, it does not determine the causality of delays caused by high temperatures because the LU data set's delay causes can only be subjectively categorized as due to heat. For example, testing the heat-related impact of failure harvesting as demonstrated with Network Rail data (Ferranti *et al.*, 2016) could not be achieved in the present research due to LU data gaps necessary for the methodology (quantitative specification of heat or temperature-related key words assigned to a particular delay).

Nevertheless, the overarching relationship between the $T\bar{C}_{\text{max}}$ and $F\bar{C}_{\text{daily}}$ for LU is comparable with that found for Network Rail (2015). This demonstrates that when observing similar trends, network benchmarking could be achievable through reporting standardization. Transport sector climate change adaptation research is considered limited by being too generic or too specific in subject matter for stakeholders to exploit (Eisenack *et al.*, 2012). What little is available at the intermediate sectoral or regional level is not yet tailored enough to meet the needs of stakeholders with minimal resources, given the appetite for "off-the-shelf" tools (Hughes *et al.*, 2009). Data standardization at the critical infrastructure scale as a holistic evidence base is, therefore, an opportunity to bridge the gap in the intermediate level of adaptation planning.

Furthermore, rail operators could benefit from publishing and reviewing their fault-reporting data with other non-rail infrastructure operators in order to understand the role of interdependencies that lead to rail delays. Faults with energy-provision networks, for instance, can cascade to influence the performance of rail networks from loss of power supply to signalling assets. Presently, the instances where externalities affect a LU delay record may not be distinguishable, as it may not be clear at the time of the incident to what the asset failure was owed. Although it would be beneficial to ensure delays are less ambiguously captured (Ferranti *et al.*, 2016), this is limited in the remit of the operating staff due to interdependencies and “known unknowns”. Delay records’ standardization from the wider infrastructure network operators could help mitigate this challenge, provided that reporting is on comparable metrics.

4.3 | Implications in the wider context of future climate change

Railway infrastructure is of growing importance as policy-makers aim to encourage a modal shift away from road vehicles to reduce greenhouse gas emissions. However, vehicle usage remains high, as its proportion of users to rail/tram/metro is disproportionate at a ratio of nearly 9:1 (European Commission, 2017). Furthermore, global infrastructure investments remain low in comparison with global population growth (MGI, 2016). Over 54% of the global population lives in urban areas, and this percentage is increasing (World Bank, 2018). Thus, demand for transport infrastructure is also very likely to increase. Therefore, if the present infrastructure still remains by the end of the century, rail-related damage costs caused by extreme weather may increase, and to a relatively greater extent than road- and aviation-related damage costs (Doll *et al.*, 2014a, 2014b). In this case, reactive adaptation stimulated by an extreme weather event (Walker *et al.*, 2015) may become more frequent. Both the public and private sectors should consider ways in which to integrate climate adaptation cost-effectively into their “business-as-usual” activity, such as following the framework outlined by Quinn *et al.* (2018) to negate these added associated financial costs.

There lies a particular challenge for rail and other transport infrastructure beyond the scope of the paper. Although the LU network is well invested and managed, a relationship between increasing high temperatures and increases in delay metrics is apparent. It is still uncertain which emissions scenario trajectory is most probable, therefore there remains a possibility that a high-emissions scenario could be reached by the end of the

century (Sanford *et al.*, 2014). In that case, the coupling of urban population growth and climate change on infrastructure could result in unprecedented pressures, and potentially lead to network-wide operational failure at high temperatures.

4.4 | Study limitations

The potential geographical inaccuracy of LU data records resulted in the absence of a spatial assessment, which would have been advantageous in this field of research. In light of the spatial sensitivity rail infrastructure has to local environmental context and conditions (Chapman *et al.*, 2006), this is a limiting factor of the present paper. The impacts of the immediate surroundings, however, such as tree or building shade, would be beneficial to validate this inference in order to uncover delay “hotspots”.

This research has been undertaken using six years of industry and meteorological data, which is a relatively short period of time from which to draw conclusions about the relationship between temperature and delays, so the present research does not attribute causality. The temperature data used here do not record the maximum at the peak time of day, a fact that would be useful to obtain for further detailed analysis in this research area. Other meteorological factors such as precipitation were omitted for the purpose of the study, and therefore the authors cannot indicate if a delay is connected to multiple weather events (e.g. a thunderstorm following a period of extreme heat). In addition, using climate projections (which themselves are subject to a degree of uncertainty) on the results from this short time period mean that the study can only provide an indication of the likely increases in delay metrics under extreme temperatures in future.

The influence of interdependencies, which were beyond the scope of the paper, further contributes to the study’s limitations.

5 | CONCLUSIONS

The approach to existing research on the impacts of weather events on rail infrastructure varies in terms of metrics. The paper recommends that publishing delay frequency and length metrics across rail infrastructure networks enables operational performance benchmarking with regards to extreme weather. This knowledge sharing on best practices to record delays could enable an improved approach to trend analysis, and the opportunity for benchmarking climate change “preparedness” in future.

The London Underground (LU) network is a globally recognizable and high-profile network facing a range of challenges, including uncertainty around climate change, capacity and future demand. To mitigate this, recommendations include further research in order to scope out risks to individual assets. As causality is yet to be determined, a macro-scale examination of the London and UK-wide interdependencies and consequential hazards that increased high temperatures may bring could shed some light on the problem. At the micro-scale, a spatial assessment of local geography and environmental conditions surrounding the infrastructure, as well as combining other meteorological events (e.g. precipitation), may aid in the identification of causality and support climate change adaptation prioritization.

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CONFLICT OF INTERESTS

The authors declare no conflicts of interest.

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