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## Estimating the frequency of trains approaching red signals: A case study for

 improving the understanding of SPAD riskYunshi Zhao ${ }^{1 *}$, Julian Stow ${ }^{1}$, Chris Harrison ${ }^{2}$<br>${ }^{1}$ Institute of Railway Research, University of Huddersfield, Queensgate, Huddersfield, UK<br>${ }^{2}$ RSSB, The Helicon, One South Place, London, UK<br>*y.zhao@hud.ac.uk

This paper describes a novel technique for estimating the frequency with which trains approach signals showing a red aspect. This knowledge is potentially important for understanding the likelihood of a signal being passed at danger (SPAD) at individual signals and also for normalisation of SPAD data, both locally and nationally, for trending and benchmarking. The industry currently uses estimates for the number of red aspect approaches based on driver surveys which are considered to have significant shortcomings. Data for this analysis is sourced from publicly available live feeds provided by Network Rail which give information on train movements and signal states. The development of the analysis model and supporting software are described and some sample results from case studies are presented. An initial study of seven signalling areas showed that approximately $3.3 \%$ of all signal approaches are to red signals. However, it also highlighted that there is a large variation in the red approach rates between signalling areas and between individual signals. SPAD risk assessment at individual signals may be significantly enhanced by the ability to estimate red approach rates for individual signals using the techniques described.

## 1. Introduction

An event where a train passes a signal showing a stop aspect without authorisation is known as a 'signal passed at danger' (SPAD). SPADs can range from minor incidents where a signal is passed by only a few metres to serious incidents where longer overruns give rise to the chance of collision with other trains. The causes of SPADs can vary widely from driver error to degraded braking performance as a result of low adhesion [1]. Driver error is frequently cited as a primary cause, often described in terms of the failure to take sufficient action at preceding warning signals ('misread') or failure to control the train on the approach to the red signal ('misjudgement') [2]. However, it is recognised that there are many underlying technical, organisational and human factors related causes which can contribute to the eventual failure of a driver to stop at a red signal [3, 4]. An example of this is the accident at Ladbroke Grove, UK, in 1999 in which there were 31 fatalities. The accident report [5] identified key failings in the design of the signalling system, signal sighting and driver training as causes of the accident.

Following Ladbroke Grove, the GB rail industry made significant efforts to reduce the rate of SPADs and the consequential risks. Since 2001, the overall risk from SPADs has reduced by $90 \%$ [6]. Figure 1 shows trends for SPADs and SPAD risk since 2006. Each SPAD is assessed using the industry's SPAD risk ranking tool [6] and assigned a score of between 0 (very low risk) and 28 (very high risk). An increase of one point corresponds to a doubling of risk. The score reflects the accident potential of each

SPAD (for example, how close it came to the potential conflict point) and the potential consequences of the accident if it had occurred (in the case of a collision, this takes into account speed, crashworthiness and passenger loadings). During 2013/14, there were 293 SPADs but only 16 of these were classified with a score of at least 20 , placing them in the 'potentially severe' risk category. These SPADs contribute the most to the underlying risk metric which is sensitive to how many of these occur in a given period. This is why the green line (showing the underlying risk) follows a different profile to the red line (showing the number of SPADs). This highlights that it is important not only to reduce the number of SPADs that occur, but also their potential severity.


Fig.1. Number of SPADs and SPAD risk - 2006 to 2014 from[4]]

### 1.1 Aims

This paper aims to show, by means of a case study, how data on train movements and signal states generated by conventional signalling systems can be used to determine how often all signals or selected individual signals are approached at danger. Initial results are presented and the potential for such data to significantly improve the understanding and evaluation of SPAD risk is discussed.

## 2. The Need to Quantify Red Signal Approaches

For a SPAD to occur, a train must approach the signal at red in the first place. It follows that knowing the number of trains which approach signals displaying a red aspect (the 'red approach rate') is fundamental to the understanding of SPAD risk at individual signals and the normalisation of SPAD data, both locally and nationally, for trending and benchmarking. SPAD risk has been studied previously using several techniques including fault tree analysis and Bayesian Belief Networks (for example by Marsh and Bearfield [7]). These techniques require a knowledge of the red approach rate to provide an accurate quantification of the resulting SPAD risk.

Nikandros and Tombs [2] note that unless SPAD count data are normalised in a meaningful way (i.e. by the red approach rate) they are not useful for benchmarking safety performance. This applies not only to international comparisons but within the same railway administration, for example when comparing suburban passenger services with long distance freight trains. Similarly, van der Weide et al [8] found their efforts to explain the apparent differences in SPAD rates for freight and passenger trains in the Netherlands frustrated by the lack of data on red approach rates and concluded that considering train kilometres alone does not constitute an adequate measure of exposure to red signals. Industry guidance from the UK and Australia further supports this view [9, 10], for example "SPADs would, perhaps, be best normalised against the 'number of red signals approached. Such data cannot be easily obtained and, by its very nature, would be affected by changes in operational circumstances" [9]. The body of published work on the causes and mitigations of SPADS contains little information on red approach rates, probably due to the difficulty in obtaining reliable data which this paper addresses. However, Nikandros and Tombs [2] present a graph showing SPAD probability versus approach rate for the Brisbane Metro area but do not explain how the red approach rate was obtained.

All these studies focus extensively on driver behaviour and the various factors which can cause SPADs but are unable to use red approach rates as a normaliser as such data is generally not available. Where normalisation is used, it is often on the basis of 'train km ' rather than the number of red signals approached which, as noted in refs $[2,8,9,10]$ is a poor normaliser. This paper proposes a method to provide reliable estimation of the red approach rate using operational data on train movements and signal states to address this problem.

## 3. Methodology

Network Rail (the GB mainline railway infrastructure manager) assesses the SPAD risk associated with every signal on the network using a process which examines the frequency and the potential consequences of passing that signal at danger. The risk assessment considers factors such as distance to a
conflict point (such as a junction), train speed and passenger loading. This process does not currently incorporate any estimates for the number of red aspect approaches to a signal within the risk assessment; however it has aspirations to do so if such information was readily available. Other tools within the rail industry have attempted to do this. The Railway Action Reliability Assessment tool [11] uses estimates for the red aspect approach rate based on driver surveys for various classes of train (suburban, inter-city, freight etc.). In this way they intend to capture the likely variation in red approach rates for different types of train service. However this approach also has some drawbacks. In particular it does not reflect the considerable variability in the red approach rate that might be expected between signals, whilst the extrapolation of relatively small surveys to give national red demand rates may not provide a reliable estimate.

Network Rail provides publicly available live data feeds which give various information on the movement of trains [12]. At the most fundamental level, the source of the information used in this paper is Train Describer (TD) data. A TD is an electronic device connected to each signalling panel which provides a description of each train (its 'headcode') and which section of track (or 'berth') it currently occupies. The TD is responsible for correctly displaying the train movements from berth-to-berth to the signaller and for ensuring that the train's identity is correctly passed to the next signaller's panel when it leaves the current signalling area.

This project used two separate TD data feeds, termed C-class and S-class messages. TD C-class messages record train movements between individual track berths, whilst S-class messages record the times at which signal aspects change. Both are transmitted through the live feed with a total of approximately 5.2 million C-class and S-class messages being sent per day. As such, it has many of the characteristics normally associated with 'big data' such as high volume, high velocity and significant value as specified by Attoh-Okine in [13]. The timestamps in TD messages are in UNIX timestamp format, which is a way to track time as a running total of seconds from January 1st, 1970. The timestamps are sent in milliseconds but the actual resolution is one second because the last three digits of all the timestamps are 0 . Figure 2 shows a train moving through two signalling berths and a possible accompanying sequence of signal aspects. Tables 1 and 2 show the train movement and signalling messages which would be generated in this simple example. Note that the S-class data only shows whether a signal is 'on', showing a red aspect or 'off' showing a proceed aspect (single or double yellow, or green).


Fig.2. Sequence of train movements and signal aspects for two track berths and three signals

Table 1 Signalling (S-class) data for the sequence of train movements shown in Figure 2

| Time | Signal 1 | Signal 2 | Signal 3 |
| :--- | :---: | :---: | :---: |
| 16:45:00 | 1 | 1 | 1 |
| 16:46:00 | 0 | 0 | 1 |
| 16:50:00 | 1 | 0 | 1 |
| 16:53:00 | 1 | 1 | 1 |
| 16:54:00 | 1 | 1 | 0 |
| $16: 54: 10$ | 1 | 1 | 1 |

Table 2 Train movement (C-class) data for the sequence of train movements shown in Figure 2

| Train | Enter | Exit | Enter | Exit |
| :--- | :--- | :--- | :--- | :--- |
| 1 F80 | $16: 50: 00$ |  |  |  |
| 1 1F80 | $16: 50: 00$ | $16: 53: 00$ | $16: 53: 00$ |  |
| 1 F80 | $16: 50: 00$ | $16: 53: 00$ | $16: 53: 00$ | $16: 54: 10$ |

At the start of the sequence, all the signals are on. At 16.46, the signaller sets a route through to signal 3 at the end of berth 2 and signals 1 and 2 clear. Train 1F80 enters berth 1 at 16.50, at the same time resetting signal 1 in the rear to red. One line of data is recorded in the C -class and S -class tables to record this. The train proceeds from berth 1 to berth 2 with the exit and entry times being added to the C-class table and the corresponding change of signal 2 back to red being recorded in the S -class data. Shortly before 16.54 , train 1 F80 approaches signal 3 at red. At 16.54 exactly, the signaller clears signal 3 and the train exits berth 310 seconds later. This example mirrors the real data in that train movement and signalling messages are separate data streams and in order to relate one to the other it is therefore necessary to know which signal is associated with which track berth. This detailed mapping is only available from Network Rail. Limited mapping is available publicly and some may be inferred by the common numbering sequences often used to describe berths and their signals.

The data itself does not provide any information about the geographical location of signals and berths, nor does it provide any information about the type of signal or the signal scheme. Some types of signals may be of particular interest when analysing red aspect approaches and local knowledge or signalling scheme plans would be required to identify these. Examples include approach controlled signals, where the signal will only clear when the train is close to the signal - often used to control approach speeds at junctions, and signals which may have subsidiary aspects or shunt signals associated with them which are also not included in the data.

## 4. Model and Software Development

The following elements were developed to carry out the analysis:

- Software to read the live feed data;
- A database to store train signalling and movement messages for subsequent analysis;
- A model to classify each signal approach within the database;
- A programme with GUI (Graphic User Interface) to allow users to set up analyses and view the results.

The interrelationship between these is shown schematically in Figure 3 and each element is discussed in the following sections.


Fig.3. Relationship diagram for the analysis process

The data flow through the analysis process is summarised in Figure 4.


Fig.4. Analysis process data flow

### 4.1 Receiving Live Feed Data

The data receiving software contains the following functions:

- Receive Network Rail messages with a STOMP client;
- Parsing the received JSON format messages into plain text;
- Write the parsed messages into an SQL server database;
- Additional functions such as error reporting.


### 4.2 Database

Microsoft SQL server is used as the database management software in this project. The Java Database Connectivity Library (JDBC) is used as the bridge between Java and MS SQL server. JDBC is a Java-based data access technology that provides methods for querying and updating data in a database.

### 4.3 Analysis Model

In order to identify red aspect approaches to signals (RAATS) in the data, it was found to be helpful to define a number of categories to classify signal approaches:

CSS - Cleared Stopped (at) Signal. The train approaches a signal at red and stops. The train departs immediately once the signal clears.

CBD - Cleared Before Departure. Applies to trains berthed in platforms where the train enters the platform with the signal displaying a red aspect. The train does not leave immediately when the signal clears, for example due to completing station work.

CAS - Cleared Approaching Signal. The signal is displaying a red aspect when the train enters the berth, but clears before the train is brought to a stand.

NRA - Not a Red Approach. The signal is off (showing a proceed aspect) when the train enters the berth.

Since, by definition, SPADs can only occur when a signal is approached at red, CSS, CAS and CBD type approaches are the main categories of interest in this study.

The analysis model uses the time at which a train enters and leaves each berth and the times at which the corresponding signals change state to classify every train approach to every signal as one of the categories above.


Fig.5. Analysis model decision tree

The model is designed as a decision tree (Figure 5). The first criterion is that the signal must follow the expected sequence by changing from a proceed aspect to a red aspect as the train passes. Any instance where this is not the case is classified as an error. After the train passes the signal aspect, the signal aspect should return to red within 60 seconds. This value is specified based on the knowledge of the railway signalling system. In the 3 -months data that are used in this case study, $97.3 \%$ records satisfy this assumption. The remaining $2.7 \%$ of records are treated as erroneous and discarded and the data is discarded. Errors in the data could arise from several sources including:

Signal mismatching: due to limited knowledge of signal - berth relationships, it is possible that on a bi-directional berth, the signal matched to the train approach faces in the opposite direction of train movement.

TD messages service error: it is possible that the either of the C -class message or the S -class message was assigned an incorrect timestamp when transmitted.

If the signal is off when the train enters the berth, the approach is classified as 'NRA'. If not, then the next step is to separate the different types of red approaches. An important criterion is the time taken to pass the signal aspect after it clears from red. In the current model, it is assumed that if this is less than or equal to 25 seconds, then it is a 'CSS' approach. Cases are classified as 'CBD' where the time difference is greater than 25 seconds and the train departs from a platform. Cases are classified as 'CAS' where the time difference is greater than 25 seconds and the train does not depart from a platform.

### 4.4 Analysis Toolkit Software

The software is developed using Java; whilst the graphical user interface (GUI) is built using SWT, which is an open source widget toolkit for Java.

The GUI (shown in Figure 6) allows the user to log on to the database and select which TD areas and signals are to be analysed, together with the time period covered by the analysis. The red approaches to a single signal may be analysed over any period from a single day to the maximum time period covered by the database, typically many months. Alternatively the user can choose to analyse all signals in a particular TD area or indeed all the TD areas in the database.


Fig.6. Red Aspect Approach Toolkit software user interface

Once the analysis has run, the user is provided with graphical output in several forms. The number of approaches to the selected signal(s) are broken down by approach type and this can be further filtered by train type (stopping passenger, express, freight empty stock etc.), this latter information being obtained from the headcode. The red approaches can also be viewed by time of day or day of the week, with similar filtering for train type. Users also have the option to compare their chosen signals with other signals. This includes an automated comparison with the top 10 signals by red approach rate in the chosen TD area(s) or with national red demand rates. Alternatively a user can create their own list of signals for comparison (e.g. all multi-SPAD signals in the area). Results for all the signals analysed can be exported to Excel for further analysis.

### 4.4 Validation

Three separate approaches have been used to verify the accuracy of the analysis model and results reporting. Initially, manual calculations were undertaken for a number of signals using the raw data from the live data feed to confirm that the analysis model correctly counts and classifies signal approaches. The manual check gave exactly the same classification results as using the analysis model.

Following this, Network Rail Control Centre of the Future (CCF) software was used to manually count signal approaches to a number of signals in the Merseyrail Electrics signalling area. CCF allows the user to replay the sequence of trains moving through a signal area, using a display which mimics the actual signaller's panel for the chosen area. CCF cannot show whether the train stopped at a red signal or not, and can only therefore confirm the correct separation between NRA and CAS/CSS/CBD events. 551 train approaches to 13 signals from the analysis model were compared to the CCF replays. 526 ( $95.4 \%$ ) of them matched the analysis model; 4 of them were not matched and 21 of them were not found in the database.

The reason for these 25 exceptions (not matching and not found) is that the data feed drops messages occasionally and therefore some train movements or signal status updates cannot be received from the server. Omitting train movement messages will lead to the 'not found' exception, and omitting signal status messages will lead to the 'not match' exception. No classification errors, i.e. NRA being labelled as CSS / CAS or vice-versa, were found.

The third approach involved several days of cab riding to generate a log of signal aspects approached and the related timings and once again these were compared to the output of the analysis model. 118 signals were passed and the model correctly classified $95 \%$ (112) of these approaches. For the remaining 6 approaches the model classified these as CSS where as observation showed them to be CAS events. This was a known issue with the time threshold approach and is discussed further in Section 6.

## 5. Preliminary Results

### 5.1 Case Study: Multiple TD Areas

The results presented in the following section are a case study based on a preliminary analysis of data from 7 TD areas (out of the possible 83) shown in Table 3. These 7 TD areas were selected due to the early availability of signal-to-berth mapping information. However, they contain a reasonably varied selection of inter-city (Watford Junction, Rugby), suburban (Merseyrail, Marylebone) and outer-suburban (Upminster, Watford Junction) TDs. The database covers all train movements in these areas over a period of approximately 3 months, in total representing around 1.8 million approaches to 892 main signal aspects.

Table 3 TD areas used for case study

| TD | Name |
| :--- | :--- |
| EA | Edinburgh IECC A |
| ME | Marylebone IECC |
| R1 | Rugby SCC (Watford - Bletchley ITD) |
| R2 | Rugby SCC (Northampton - Rugby ITD) |
| SS | Merseyrail |
| U3 | Upminster 3 IECC |
| WJ | Watford Junction |



Fig.7. Classification of all signal approaches in 7 TD areas over a 3-month period

Figure 7 shows that $3.3 \%$ of all signal approaches were to a red signal (i.e. in the CSS or CBD categories) and this alone is a useful headline figure. However, even a relatively crude breakdown by individual TD area, shown in Figure 8 highlights some important differences.


Fig.8. Breakdown of red signal approach rate and total number of signal approaches by TD area over a 3-month period

The Rugby signalling panel R1 on the West Coast Mainline and Merseyrail panel SS have the highest number of train approaches to signals of the TD area examined at 434,176 and 411,499 respectively for the three month period. R1 and R2 which are on the West Coast Mainline have the lowest red approach rates at $1.5 \%$ In contrast the remainder of the TD areas, which all include a high proportion of suburban traffic, have combined red approach rates for the CSS and CBD categories varying between $2.5 \%$ and $6.9 \%$. These results, which show that red approach rates can be more than three times higher in some areas than others, have important implications when considering normalising and trending of SPAD data. They suggest that use of more localised red approach rates may be beneficial in increasing the accuracy of such calculations.

### 5.2 Case Study: Single Signal

This section examines the results for a single signal. ET776 signal is located on the up Cowdenbeath line at Redford and was chosen as it has been the subject of two separate SPADs on 13/7/11 and 30/1/14[14]. Figure 9 shows that after passing ET776, trains can take one of three routes:

- Remain on the Up Cowdenbeath line toward signal ET772;
- Cross over to the Down Cowdenbeath line toward signal ET774;
- Cross over both lines to the carriage sidings.


Fig.9. Signal plan for ET776 signal

Figure 10 shows that at $16 \%$, the red approach rate is more than eight times higher than the average rate ( $2 \%$ ) from the multi-area study discussed above. It is also more than six times higher than the red approach rate for the Edinburgh IECC-A TD area within which it is located. Figure 11 shows the red approach rates broken down by train headcode (type) on the primary y -axis whilst the secondary y -axis shows the total number of approaches to ET776 signal by train type.


Fig.10. Classification of all signal approaches to ET776 signal over a 3-month period


Fig.11. Breakdown of red signal approach rate total number of signal approaches for ET776 signal over a 3-month period (note: 'national' values are derived from the study of 7 TD areas as shown in Figure 9)

The highest number of approaches to the signal (711) was by class 2 (H2 - ordinary passenger) trains but the red approach rate for these trains was zero. In contrast, only 286 approaches to the signal were by class 5 trains (H5 - empty coaching stock) but the red approach rate to ET776 signal for this class of train was more than $80 \%$. The data was further analysed by the route and it is found that more than $80 \%$ ( 233 out of 286) of empty coaches went on the Down Cowdenbeath line or to the sidings. All of these 233 train approached ET776 showing a red aspect. All class 2 trains remained on the Up Cowdenbeath line. This example illustrates that red approach rates at individual signals can vary widely from the average values, either nationally or from a particular TD area. It also shows that geographic and/or operational factors, especially the routes can significantly alter the conditions under which red approaches occur. This has significant implications for the understanding and calculation of SPAD risk at individual signals. Not only does it permit the risk to be based on the individual red demand rate for a particular signal, but it also offers the possibility of refining the modelling for a signal. In this example the majority of red approaches are by empty stock and freight trains and it is therefore more likely that one of the trains involved in a potential collision following a SPAD would not be carrying passengers.

## 6. Limitations

The case study presented in this paper is based on GB mainline signalling systems, practice and TD data. It is a fundamental principle of all modern signalling systems that the positions and identity of trains and the state of signals must be known. The techniques presented in this paper are therefore broadly applicable to any modern signalling system. However, there will inevitably be differences in the implementation of TD devices and the information technology and data layers which surround them which would require the RAATS Analysis Toolkit software to be adapted accordingly.

The GB mainline rail network has 146 TDs providing C-class data but only 82 also provide S-class data. As discussed, only areas providing S-class data can be included in the red aspect approach analysis. Currently some highly trafficked areas of the network are omitted, for example Crewe, Doncaster and Kings Cross TDs do not report signalling data. Coverage will increase as new signalling schemes are implemented.

A separate database is used to identify if a berth is on a station platform. However, the validation exercise highlighted that this database omits some minor stations. This can result in some 'CBD' events being miss-classified 'CSS'. As both types of event have the potential to result in a SPAD, this does not
change the overall results but nonetheless remains a limitation until a more comprehensive database can be obtained.

The current analysis model separates CSS events, which have the potential to cause a SPAD from CAS approaches, which do not, by means of a time threshold as described in Section 4.3. Whilst this has been shown to be reasonable, there will be some train approaches where the signal cleared within the threshold time (i.e. while the train was still moving slowly on approach to the signal) which will be incorrectly classified as CSS. Work is ongoing to refine this part of the model to improve the differentiation between CSS and CAS events, although this is difficult with the limited data provided by C and S-class messages alone.

## 7. Further work

A key element of future work is improving the ability of the model to discriminate between 'CSS' and 'CAS' events. Several options exist for this, depending on the addition information available. Simply knowing the length of each berth would permit the berth transit times to be used to compare the likely approach speed with an idealised braking curve. This would permit better discrimination between trains which were likely to have stopped and those where the signal was likely to have cleared when the train was relatively close to it. It is thought that some uncertainty will always remain even with an enhanced model but that this can be reduced significantly.

Once these refinements have been completed, it is intended that the tools described in this paper will be used to provide more accurate estimates of national red approach rates than those presently used for various train classes. It is also intended to investigate the red approach rates for signals where SPADs have occurred and to further consider how the ability to determine individual approach rates can be used to better understand the distribution of SPAD risk in the current signal risk assessment process.

## 8. Conclusions

An analysis model and software tool have been developed that allows the number of red signal approaches to be determined at individual signals, groups of signals or over a whole TD area or many TD areas.

The tool provides the basis for a better understanding of SPAD risk at individual signals and for improved normalisation of SPAD data for trending and benchmarking nationally.

Preliminary results for 7 TD areas showed that approximately $3.3 \%$ of all signal approaches are to red signals. However, it also highlighted that there is a large variation in the red approach rates between

TD areas and between individual signals. Further refinement of the model may be required to improve how CAS type approaches are separated from CSS type approaches.

The analysis presented in this paper could also be extended in future to provide detailed information regarding train routing at junctions which is also a significant factor in the possible consequences of a SPAD. It also offers the potential to provide knowledge which is useful in driver training. Whereas the current analysis has concentrated on the red approach rates at individual or groups of signals, it would also be possible to analyse this for individual train workings (using the headcode) which could yield valuable information on the robustness of timetables and the sources of operational delays on the network.

## 9. Acknowledgment

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