Can Link Analysis Be Applied to Identify Behavioral Patterns in Train Recorder Data?

Journal Item

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Version: Accepted Manuscript

Link(s) to article on publisher’s website:
http://dx.doi.org/doi:10.1177/0018720815613183

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Can link analysis be applied to identify behavioural patterns in train recorder data?

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ACKNOWLEDGEMENTS

This work was funded by the UK Economic and Physical Sciences Research Council (EPSRC) under Grant Reference: EPSRC EP/I036222/1. The involvement and support of the UK Rail Safety and Standards Board (RSSB), the Association of Train Operating Companies (ATOC), and Greater Anglia Trains is gratefully acknowledged.

KEYWORDS: Leading indicators; Link Analysis; Graph Theory; Data recorders; Driving
ABSTRACT

Objective: A proof of concept analysis was conducted to establish whether link analysis could be applied to data from on-train recorders to detect patterns of behaviour that could act as leading indicators of potential safety issues.

Background: On-train data recorders capture data about driving behaviour on thousands of routine journeys every day, and offer a source of untapped data that could be used to offer insights into human behaviour.

Method: Data from seventeen journeys undertaken by six drivers on the same route over a sixteen hour period were analysed using link analysis, and four key metrics were examined: Number of links, Network Density, Diameter, and Sociometric Status.

Results: The results established that link analysis can be usefully applied to data captured from on-vehicle recorders. The four metrics revealed key differences in normal driver behaviour. These differences have promising construct validity as leading indicators.

Conclusion: Link analysis is one method that could be usefully applied to exploit data routinely gathered by on-vehicle data recorders. It facilitates a proactive approach to safety based on leading indicators, offers a clearer understanding of what constitutes normal driving behaviour, and identifies trends at the interface of people and systems, which is currently a key area of strategic risk.

Application: These research findings have direct applications in the field of transport data monitoring. They offer a means of automatically detecting patterns in driver behaviour that could act as leading indicators of problems during operation, and which could be used in the pro-active monitoring of driver competence, risk management and even infrastructure design.
PRÉCIS

Link analysis was applied to data collected from on-train recorders and four metrics drawn from graph theory were calculated. The results offer a proof of concept of the potential to use these data to detect patterns of behaviour that could act as leading indicators of potential safety issues.
INTRODUCTION

On July the 6th, 2013, a Boeing 777 crashed on landing at San Francisco Airport, resulting in the deaths of three people, and the injury of 181 others (NTSB, 2014); on July the 22nd, 2013, a ‘hard landing’ by a Boeing 737 at New York’s LaGuardia Airport injured sixteen passengers (NTSB, 2013); on the 24th of July, 2013, one of the most serious train accidents in Spain’s history occurred in Santiago de Compostela, resulting in the deaths of 79 people, and causing injury to many more (Puente, 2014). While the occurrence of three such events in the space of a month may suggest transport incidents of this type are commonplace, in reality, accidents in these sectors are extremely rare. Since the 1940s safety performance in most transport and high hazard sectors has improved dramatically (Shappell & Wiegmann, 2004; Evans, 2011, 2012; EASA, 2010). A side effect of this trend, however, is that a different type of accident, which identifies the critical role of the human in the system, has been exposed. As with the three accidents that occurred in July 2013, these accidents typically occur in spite of fully functioning equipment and world-class safety management processes (e.g. NTSB, 2013, 2014; Puente, 2014). This represents a major challenge for safety and Human Factors disciplines.

Lagging Indicators

One of the defining technical developments at the heart of improving post war trends in safety is the so-called ‘Black Box’. Although there is a long history of using devices for mechanical ‘condition monitoring,’ it was the development of the cockpit voice recorder that seized the imagination of a nascent airline industry seeking methods of tackling notable airline crashes (Warren, 1954). ‘Black Boxes’ (or more correctly, data recorders) automatically capture information about changes to system parameters over the course of a
journey. In the UK and US, airliners have been required to carry ‘Flight Data Recorders’ (FDR) since the 1960s. In the UK, trains have had to carry similar ‘On Train Monitoring and Recording’ (OTMR) devices since 2002. The original purpose of these instruments was to supply data that could assist investigators in understanding the causes of an accident, and offer a means of learning from this in order to prevent a re-occurrence. In these circumstances the recorder data are used as a ‘lagging indicator,’ a type of loss metric that is apparent only after an incident has taken place (Rogers, Evans & Wright, 2009).

A side effect of improving safety trends, however, is that the volume of data collected from data recorders in normal operations is now vastly out of proportion to that required to diagnose the cause of a specific accident. The original ‘flight memory unit’ dating from the 1950s could monitor eight channels of information on a four hour self-erasing loop. Today, most modern airliners, using the industry standard ARINC 573 avionics standard, record in excess of 2000 parameters on quick access storage mediums, which, for most practical purposes, are unlimited. The situation is therefore a paradoxical one. The volume of data collected via ‘black boxes’ has never been so abundant, yet because accidents are so rare, the opportunities to use the data, at least for the original purpose of post-accident analysis, are equally rare. This creates a large but significantly under-used source of data, and if, for each infrequent major accident, there are many more ‘incidents’ like Signals Passed at Danger (SPADs) (on the railways) or long landings (in aviation), then a focus on major accidents, or ‘loss metrics’, could be misdirected (Bird & Germain, 1985; Heinrich, 1941; Coury et al., 2010; Eurocontrol, 2013, 2014). This raises the possibility of a complementary approach, using this vast store of recorder data to identify measurable precursors to major events. These are termed ‘leading indicators’ and form part of a new paradigm in risk control and predictive safety (e.g. Eurocontrol, 2013, 2014).
Leading Indicators
Leading indicators are based on the underlying concept of risk triangles developed within the insurance industry (see Heinrich, 1941). Heinrich used data from real accidents in the 1930s, and established empirically that for every major accident in which an injury or fatality occurred, there were 300 recordable incidents that did not result in injury. The improvement in post war safety performance is evident in aviation data, which today shows the base of the risk triangle comprising 49,000 ‘occurrences’ yet only 179 ‘serious incidents’ (CAA, 2011). Many similar risk pyramids in other domains possess extremely wide ‘bases’ of ‘no injury accidents’ and extremely narrow tips of ‘major injuries’. The broader principle at work here is that for every major incident there are many more precursor events (Bird & Germain, 1985), that each of these precursors has the potential to develop into a serious accident given the wrong combination of circumstances, and that these precursor events will be contained in the data recordings routinely collected, but often not systematically analysed.

Safety Plateau
A concerning feature of accident data in the rail and aviation sectors is that while the frequency of major accidents is low, the rate has remained relatively stable despite technological advancements in safety equipment and procedures (European Aviation Safety Authority (EASA), 2010; Wolmar, 2012). Further, the desired reduction in less serious incidents has not occurred in aviation (Civil Aviation Authority (CAA), 2011) or rail sectors (Wolmar, 2012). Indeed, in the rail sector “there is widespread concern within the industry that the background indicators – rather than the headline grabbing ones – have remained worryingly stable” (Wolmar, 2012). Although delays in applying appropriate safety features may contribute to issues on the railways (e.g. Rail Accident Investigation Branch (RAIB),
2008), as in aviation, improved safety equipment is not a panacea, and an examination of the ‘broad causes’ implicated in recent rail and aviation accidents provides evidence that the interface between human and technology is critical. Based on an analysis of global aviation accidents, the UK Civil Aviation Authority’s 2011 Safety Plan (CAA, 2011) identified seven key safety issues. The top four (Loss of Control, Runway Excursions, Controlled Flight Into Terrain, and Airborne conflict) relate strongly to Human Factors issues. The accident discussed in the introduction, where a Boeing 777 landed short of the runway at San Francisco airport and hit the seawall that precedes it, falls broadly under the third category - Controlled Flight into Terrain (CFIT). The safety systems were functioning and the crew was seemingly in control of the aircraft when the accident occurred. In this case the lagging indicator is the occurrence of an accident that can be formally examined in detail. The leading indicators might be an observed increase in the number of planes landing at some point before the ideal touchdown area, or some other subtle features of the situation or context that shapes behavior in undesirable ways, which can be detected from the data provided by hundreds of routine journeys.

Similarly, in an analysis of European rail accident data, three of the seven ‘broad causes’ listed (Signals Passed at Danger, Overspeeding, Signalling/Dispatching error), also involve a prominent Human Factors dimension (Evans, 2011). For example, overspeeding was identified as a factor in the train accident in Santiago de Compostela (Puente, 2014). In this instance, the combination of circumstances meant that the consequences of over-speeding were severe. However, a large number of less extreme speed violations in this area of track could also serve as leading indicators and help identify the potential danger before it results in an accident of this magnitude.
In pursuit of further safety enhancements, and recognising the paradoxes exposed by improving safety trends, the UK Civil Aviation Authority pioneered an innovative approach to the analysis of recorder data called Flight Data Monitoring (FDM) or Flight Operations Quality Assurance (FOQA). In FDM, data from on-board recorders are extracted and analysed after every journey with the explicit aim of detecting subtle trends that may be indicative of future problems (Wright, 2012). The approach is structured around the detection of leading indicators or ‘events’, which are defined as: “deviations from flight manual limits, standard operating procedures and good airmanship” (Civil Aviation Authority (CAA), 2003, p16). Under ICAO Annex 6 Part 1 (Amendment), Flight Data Analysis is now mandatory for operators of aeroplanes of a certified take-off mass in excess of 27,000 kg. The safety culture in the comparable UK rail industry is perhaps less mature, but the importance of leading indicators is encouraged via the Rail Safety and Standards Board safety culture toolkit (RSSB, 2011).

While the concept of leading indicators is well accepted, the challenge is to apply this concept to the Human Factors risks that are now of most strategic concern; Neither the rail nor aviation sectors are able to do this in a comprehensive and robust way, and there is considerable scope for innovation. This paper describes a novel means of contributing to progress in this area, by linking data recordings to human factors methods, in order to develop proof of concept human factors leading indicators.

Link Analysis

Link Analysis is an interface evaluation method used to identify and represent ‘links’ in a system between interface components and operations, and to determine the nature, frequency
and importance of these links (Chapanis, 1996; Stanton et al., 2005). Links are movements of attentional gaze or position between parts of the system, or communication with other system elements. For example, if an actor is required to press button A and then button B in sequence to accomplish a particular task, a link between buttons A and B is recorded. Link analysis uses network diagrams to represent the links within the system or device under analysis, with each link represented by a straight line between the ‘linked’ interface elements or ‘nodes’. The most obvious use of link analysis is in the area of workspace-layout optimisation (Stanton & Young, 1999) where it provides information on the placement of controls and displays according to their importance, frequency of use and function.

Link analysis was originally developed for use in the design and evaluation of process control rooms (Stanton & Young, 1999), but it can be applied to any system where the user exhibits hand or eye movements, including driving a train or piloting an aircraft. The approach is extended in this paper by relating it more generally to the fields of Graph Theory, a well-established branch of applied mathematics with a long history of application in many different domains, which operates on data matrices of the sort that underlie link analysis. Instead of viewing a link analysis diagrammatically as a series of ‘nodes’ and ‘links’, graph theory can instead be applied to a matrix which describes the link diagram as a form of cross tabulation table (an example is shown in Figure 1). The table has two axes along which all the nodes are arranged. If nodes along these axes are linked, then a value is inserted into the appropriate intersecting cell within the matrix. Graph theory is used to extract numerical metrics that can reveal useful underlying properties of the link analysis that cannot be detected by visual inspection alone. This approach has been used successfully by researchers in organizational design, most notably Bavelas, Leavitt, and colleagues at MIT in the 1950s and 60s (e.g. Bavelas, 1950; Bavelas & Barrett, 1951; Leavitt, 1951 who were able to use
A Novel Application of On Train Data Recordings

In the current application, rather than using observation, link diagrams will be driven directly from recorder data by monitoring the channels that record the activation of controls that are manipulated by human operators. By these means the range of ‘normal’ patterns of interaction with the controls can be defined, reflecting individual differences and environmental factors. The prediction is that these outputs, which could be generated automatically in a full-scale application, will provide metrics that help the analyst to discern important features of the pattern and structure of human interaction with a control interface.

This investigation therefore acts as a ‘proof of concept’ to establish the potential of the approach using ‘real-world’ train data, and to consider whether it could offer useful insights if applied on a larger scale within both the rail and aviation sectors. The following sections detail the specifics of the approach, the range of metrics applied to the link analysis data, and the results obtained.

METHOD

Dataset

A sample of transport recorder data was provided by a UK train operating company in the form of a continuous download from a Class 153 ‘Super Sprinter’ diesel passenger multiple unit. The On Train Data Recorder (OTDR) device was a UK Group Standards compliant Arrowvale unit that recorded 72 parameters. The recorder scans the parameters for changes at a rate of 20ms but in the present system, to economise on memory requirements, data are only logged when one of the 72 parameters changes. The ‘raw’ data file, therefore, contains a
non-uniform timeline that was corrected in manual post processing. For this proof of concept
demonstration 17 recorder channels were monitored. These referred to all of the primary
driver controls, from brake and throttle controls to the door release button and train horn,
including all the relevant safety systems. The data recordings covered six drivers who
undertook 17 journeys on the same route on the same day. For confidentiality and to comply
with ethical guidelines, further details of the individual drivers were not provided. The first
journey commenced at 7.01 am and the last commenced at 11.01 pm. The journeys took
place in Eastern England on a rural branch line. This route, combined with the rolling stock
chosen, offered a particularly well controlled environment, although it should be noted that
the route has a particularly high incidence of accidents and incidents (including several level
crossing collisions and an impact with the buffer stops: these incidents are not part of the
current data file). The line begins at a station called Marks Tey and terminates 13km later at
a station called Sudbury. The analysis was based on the final portion of the journey, from the
penultimate stop in Bures until termination of the journey in Sudbury, a distance of 7 km. On
this section of route the maximum speed is 50mph, the gradients are gentle, and trains operate
on a ‘single train only working’ basis. In other words, there are few sources of external
variation on the route between Bures & Sudbury station, so observed differences in the
interactions between driver and interface will be indicative of differences in driving

Procedure

Link analysis is used to analyse the way in which drivers interact with the train controls,
recording the presence or absence of relationships among pairs or sequences of controls. For
example, if a driver moves the brake from Step 3 to Emergency, this creates a direct link
between these two control positions. The two brake positions would be represented as nodes
in the resultant diagram, with a line between them to show they are linked. If the brake is never moved directly from Step 1 to Step 3, but always passes through Step 2, then there will be no direct link between the two, though a longer path (Step 1 to 2, Step 2 to 3) will exist. The operating principles that underlie link analysis can be seen more fully in Figure 1. Link analysis, and calculation of corresponding network metrics using Graph Theory, was conducted on each of the seventeen journeys. This produced an individual link matrix table for each journey, a combined master matrix where the pattern of control activities was summed across all seventeen journeys, and six ‘driver’ matrices, which combine data across journeys to identify the patterns of interactions exhibited by each of the six drivers separately. The link matrices, and corresponding graph theory metrics and link diagrams, were implemented in a software package called Applied Graph and Network Analysis (AGNA) (Benta, 2003). Four metrics of interest were produced: number of links (the total number of control inputs used to drive the train from the origin station to the destination), network density (the portion of all possible links in a network that are actually linked), diameter (the number of links required to travel between every pair of nodes in the network, i.e. the longest of all the calculated path lengths), and sociometric status (a measure of the ‘connectedness’ of nodes in the network, a measure of their importance). These metrics are explained in more detail in the sections that follow, but Figure 1 summarises the way in which link analysis was applied.
Figure 1: Diagram illustrating the application of link analysis and how a sequence of control actions can be visualized as a set of nodes and links in a network diagram and link matrix table.
RESULTS AND DISCUSSION

Network Diagrams

The pattern of control activities across all 17 journeys is summarised in the network diagram in Figure 2. This gives a visual representation of the pattern of connections that were produced across all drivers and journeys in the analysis. This link diagram demonstrates that some components of the cab interface are more heavily interconnected than others, that there is an ‘overall’ level of connectivity, and that the number of links one needs to traverse to reach different pairs of nodes (controls) also differs.

Figure 2: Overall Network Diagram showing the sum of all links based on 17 journeys between Bures and Sudbury (n = 6 drivers). The links are binary and denote the presence of a link in one or more journeys/drivers.
To investigate whether individual drivers differ in their interactions with the cab interface and controls, network diagrams were also produced for each of the six drivers, and these are shown in Figure 3. The diagrams are formed based on the journeys undertaken by each driver, which varies from two to five trips. Drivers 2, 3, and 5 undertook two journeys each, Drivers 1 and 4 undertook three journeys each, and Driver 6 undertook five of the journeys. Despite these differences, the links in the network are binary, so the number of times the same link occurs (which will naturally be higher over a greater number of journeys) does not affect the analysis.
Figure 3: Individual driver network diagrams showing the distinct ways in which drivers interacted with the train controls while covering the same route.
All journeys took place on the same day, on a relative simple route, and this is reflected in the similarities that can be seen across the driver diagrams. However, it is still possible to observe different patterns of links in the network diagrams of the six drivers. For example, the network diagrams of Drivers 3 and 5 exhibit distinct patterns of connections. It can be seen that Brake Stage 3 is linked to a greater number of nodes for Driver 5 than for Driver 3, and the pattern of interactions in relation to braking appears different more generally despite the common route followed. Clearly the method is sensitive to small differences in behavior. Graph Theory was applied to formalise these differences by performing a mathematical analysis of the link matrices using four different network outputs.

**Number of Links**

The first, and most simple, network metric is the number of links. The number of binary links across the 17 journeys ranged from 24.8 (Driver 6) to 34 (Driver 4).

![Figure 4: Spread of link values across journeys and drivers](image-url)
The differences in the number of links across driver networks suggest there is variation in the way in which the drivers interact with the interface. Networks with a greater number of links have connections between more node pairs, and this may indicate that in these networks the driver uses the controls in a more flexible manner (e.g. sometimes moving the speed controller from position 4 to 5, sometimes from 4 to 7). Looking at the means, there does not appear to be a consistent pattern, but there are individual differences. Driver 6 has the lowest mean link value ($M = 24.8$), while Driver 4 has the highest value ($M = 34$). To explore this further, the link values for each journey, separated by driver, are also displayed in Figure 4. On closer inspection of the individual variation, it appears that Driver 6 has low link values across journeys, which suggests this individual is fairly consistent in their interactions with the controls. Meanwhile, Driver 4 records different values for each of the three journeys undertaken. While other external changes in lighting etc. may explain some of these differences, there is support for the idea that this metric offers potentially important insight into individual differences in driving style.

The present method shows promise as a means of detecting leading indicators, as it appears sensitive to differences in behaviour between drivers on the same route. Some variation is evident even with a small sample of data on a series of relatively straightforward single-track journeys, but further investigation is required to assess the effectiveness of different driving strategies on a larger scale. By comparing driver performance across repeated journeys on the same route, it may be possible to establish the range of ‘normal’ performance for an individual driver, and for all drivers on the route. Where performance on a particular journey deviates from these norms, this information may act as an indicator that something is amiss before an accident occurs. This could be a useful means of monitoring fatigue on routes.
where environmental conditions have been identified as problematic, by offering objective evidence to support driver reports.

Density

The second network metric is ‘density’, and measures the actual number of links used compared to the maximum available. It is given by the formula:

\[
\text{Network Density} = \frac{2l}{n(n-1)}
\]

Where ‘\(l\)’ represents the number of links in the diagram and \(n\) is the number of individual interface items. The value of network density ranges from 0 = no interface items connected to any others, through to 1 = every interface item is linked to every other at some point in the journey. Figure 5 illustrates the spread of values for the current sample of six drivers on an identical route. It shows that density varies between 0.09 (Driver 6) and 0.12 (Drivers 1 and 3) with a mean of 0.11.

\[\begin{array}{cccccccc}
\text{Driver 1} & \text{Driver 2} & \text{Driver 3} & \text{Driver 4} & \text{Driver 5} & \text{Driver 6} \\
(n=3) & (n=2) & (n=2) & (n=3) & (n=2) & (n=5) \\
\text{Density} & 0.12 & 0.11 & 0.10 & 0.12 & 0.10 & 0.09 \\
\end{array}\]

\text{Figure 5: Network density by driver}
High density, broadly speaking, suggests a pattern of interaction characterised by a large response repertoire. To illustrate, in a fully connected network control actions could follow any sequence, because all actions would be possible. In the current network, it would mean that, for example, after releasing the brakes the driver could potentially perform any other interaction with the interface. In practice, only some combinations occur, producing differently connected networks. Where a network has high density there are lots of options for different control sequences, the context requires and/or is compatible with these different control sequences being deployed and, furthermore, the driver has the requisite skills and sensitivity to the environment to be able to perform them. Whether high or low response diversity is objectively ‘good’ or ‘bad’ depends on the circumstances and risk outcomes derived from larger scale analyses. In this analysis, there is little variation in density values across drivers. However, given the restricted nature of the track followed on this journey, this is not surprising. If a value were recorded that fell outside this narrow range, then this may also provide a leading indicator that the driver’s task performance has deviated from that expected on this route.

**Diameter**

The third network metric is called ‘diameter’, and is given by the formula:

\[ \text{Diameter} = \max_{u,v} d(u,v) \]

Where \( d(u,v) \) is the greatest number of individual controls that have to be negotiated in order to progress from one control to another, excluding routes that backtrack, detour, or loop (Weisstein, 2014; Harary, 1994). Put more simply, diameter represents the longest path in the network in terms of the number of nodes that are traversed. The chart in Figure 6 shows that
mean network diameter varied between 8.33 (Driver 4) and 11.5 (Driver 5). Across drivers, the mean diameter was 9.82.

Generally speaking, larger diameters are associated with more ordered sequences of activity, and the difference between Driver 4 (diameter = 8.33) and 5 (diameter = 11.5) indicates a difference in their interactions with the controls. This means that on average the longest path between any two connected nodes in the network is three links longer for Driver 5 than for Driver 4. To give an example of what this difference means in practice, examination of the data for the two journeys undertaken by Driver 5 reveals that each time the driver accelerated the train, the controls were used in a consistent step-like manner. When moving from throttle position 0 to 7, each intervening position was used, in the order 0-1-2-3-4-5-6-7 (diameter =7). However, when the three journeys undertaken by Driver 4 are examined, a different pattern is visible. This driver does use the 0-1-2-3-4-5-6-7 some of the time when accelerating the train from throttle 0 to 7, but a different pattern is also used. On half of the accelerations (6 out of 12 instances), the driver moves the throttle in the order 0-1-2-3-4-7.
Running Head: Link analysis and train recorder data

(diameter = 5). This means that the driver uses fewer steps to move between 0 and 7 on these occasions, which contributes to a smaller diameter. The current analysis does not attach a value to these differences, as high levels of sequencing may be entirely appropriate in certain contexts, but less appropriate in others, and an analysis of outcomes based on a larger dataset is required to determine this. The key issue is that the method is sensitive enough to be able to capture these subtleties.

Sociometric Status

The fourth network metric is ‘sociometric status’. Sociometric status provides a measure of how active a node is relative to the total number of nodes in the network (Houghton, et al. 2006). Nodes that are highly connected to other nodes in the network will have high sociometric status. This is calculated using the formula:

\[ \text{Sociometric Status} = \frac{1}{g-1} \sum_{j=1}^{g} (x_{ji} + x = ij) \]

Where \( g \) is the total number of nodes in the network, \( i \) and \( j \) are individual nodes and are the link values from node \( i \) to node \( j \). In this context sociometric status metric was used to identify the relative importance of nodes across different journeys and drivers. Sociometric status provides a measure of how active a node is relative to the total number of nodes in the network (Houghton, et al. 2006). Nodes that are highly connected to other nodes in the network will have high sociometric status.

A sociometric status analysis was conducted for each of the 17 individual journeys between Bures and Sudbury. Using these values a mean score was calculated for each driver based on
the journeys for which they were responsible. The results of these calculations are
summarised in Figure 7 along with the mean across all 17 journeys. Although the data are not
continuous, the use of a line chart helps to illustrate the differences between drivers, and the
sociometric status of each control.

Figure 7: Sociometric Status values by driver showing mean (solid black line) and all
6 drivers (LEFT) and the mean versus drivers 4 and 6 (RIGHT)

The different patterns that emerge can be more clearly seen in the right hand side of Figure 7,
which displays data from two of the drivers, Driver 4 and Driver 6, and compares their
performance against mean performance across all 17 journeys. This graph shows that the two
drivers display different signatures from each other, and these also differ from mean
performance. This can be seen most clearly in the values for the throttle positions. In all three
profiles there is an overall pattern of descending importance as the throttle position increases,
however, the values for Driver 6 are consistently lower than the mean. In contrast, the values
for Driver 4 are higher than those of Driver 6 throughout, and higher than the mean for all
throttle positions except for throttle position 2. There is also a small peak at throttle position 4, which shows this node has higher importance for Driver 4 than for Driver 6 (and the mean).

By examining the OTDR data files for the three journeys undertaken by Driver 4 and the six journeys undertaken by Driver 6, the underlying differences in the way in which these drivers interact with the throttle are revealed. Table 1 displays descriptive statistics that summarise three key measures of throttle use for these drivers and shows that there are key differences between the drivers.

Table 1 Interactions with the throttle controller for Drivers 4 and 6.

<table>
<thead>
<tr>
<th></th>
<th>Driver 4</th>
<th>Driver 6</th>
</tr>
</thead>
<tbody>
<tr>
<td>No. of sequences per journey</td>
<td>11</td>
<td>6</td>
</tr>
<tr>
<td>Mean no. of throttle moves per sequence</td>
<td>5.81</td>
<td>3.87</td>
</tr>
<tr>
<td>Mean no. of throttle moves per journey</td>
<td>64</td>
<td>23.2</td>
</tr>
</tbody>
</table>

Driver 4 initiated 11 sequences of throttle movement on each of the three journeys undertaken, while Driver 6 initiated 6 sequences of throttle movement on each of the five journeys undertaken. Additionally, the sequences initiated by Driver 4 ($M = 5.81$) consisted of a greater number of steps than those initiated by Driver 5 ($M = 3.87$), and during the journey from Bures to Sudbury, Driver 4 altered the throttle position an average of 64 times, versus an average of 23.2 times for Driver 6. Distinct patterns such as these indicate again that this metric offers a useful means of identifying different ways in which drivers interact with the controls, and suggests these differences may grant access to leading indicators
around driver strategy and technique that could usefully inform safety improvement and eco-
491 driving strategies. For example, it may be possible to identify if over-speeding incidents are
more likely to occur for drivers who use one method of driving than another. The key issue
493 going forward is to map the performance of these different link-based metrics to actual risk
494 outcomes, and formally establish their performance as robust human factors leading
495 indicators. As a first step towards this goal a set of candidate leading indicators, such as
496 those described above, are needed.
497

CONCLUSION

The aims of this paper are to assess whether human factors methods like link analysis can
499 accept recorder data as an input, whether graph theory can be usefully applied to the data
500 matrices underling the method, and to identify a set of candidate leading indicators that
501 appear sensitive enough to detect subtle changes in driver behavior. Each of these aims has
502 been met, so the next step is to apply these candidate leading indicators to a larger data set,
503 and formally establish the relationship between them and actual risk outcomes. To operate
504 effectively as a leading indicator the method used should be methodologically robust (i.e. it
505 should provide meaningful insights into actual risk outcomes), practically expedient (i.e.
506 amenable to automation, given the potentially large quantities of data involved), and couched
507 firmly at the interface of people and systems (this is where most strategic risks now seem to
508 reside). As an established Human Factors method (e.g. Stanton et al. 2005), link analysis
509 fulfills the first criterion, and the analysis presented here demonstrates it has the potential to
510 satisfy the second and third.
Marked differences in driver behavior would not be anticipated over such a simple route, using identical rolling stock, and performed on the same day. Indeed, the ‘outputs’ of the driver’s control actions resulted in identical outcomes: the train departed and arrived on time, and adhered to the speed limit and other route constraints at all times. Within this, however, were some marked differences in how this outcome was achieved, which the link analysis method was sensitive enough to capture. The distinct patterns of interaction evident in the network diagrams hint at how little we know about what constitutes ‘normal’ driver behaviour or the antecedents of more serious incidents and accidents, which reside within it. The current state of practice in driver training and competence is heavily orientated around observation, classroom training and to some extent driving simulators. Approaches like the one described in this paper highlight the opportunities to be gained from a continuous process of data monitoring using metrics that are simple to automate and that are sensitive to human factors aspects of driver behaviour. The possibilities to for using approaches like this within existing competence management systems, and to inform non-technical skills training, are considerable. Large quantities of ‘big data’ already exist and the data collection infrastructure is already in place. What are currently missing are the human factors leading indicators with which to convert these raw data into practical insight. This paper represents a step in this direction.

**KEY POINTS**

- Transportation accidents occur in spite of the well-developed safety mechanisms in operation, and the human factors component of operational safety is of increasing importance.
On-train data recorders capture data about driving behaviour on thousands of routine journeys every day, which could potentially be analysed using Human Factors methods in order to develop leading indicators.

The data source offered by on-vehicle recorders can be used pro-actively to improve safety in both aviation and rail transportation.

This article presents four metrics from graph theory analysis (links, density, diameter, sociometric status) applied to data from on-train data recorders that offer a proof of concept of the potential to use these data to detect changes in driver behavior.
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