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DOI

[10.1016/j.ifacol.2018.07.020](https://doi.org/10.1016/j.ifacol.2018.07.020)

Publication date

2018

Document Version

Final published version

Published in

Proceedings of 15th IFAC Symposium on Control in Transportation Systems (CTS 2018)

Citation (APA)

Xie, W., Nunez, A., Maas, R., & Li, Z. (2018). Decision support tool based on multi-source data analysis for the tram wheel-rail interface. In B. De Schutter, & A. Ferrara (Eds.), *Proceedings of 15th IFAC Symposium on Control in Transportation Systems (CTS 2018): Savona, Italy, June 6-8, 2018* (9 ed., Vol. 59, pp. 118-123). (IFAC-PapersOnLine; Vol. 51, No. 9). Elsevier. <https://doi.org/10.1016/j.ifacol.2018.07.020>

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Decision support tool based on multi-source data analysis for the tram wheel-rail interface

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Abstract: This paper presents a methodology to support decision making based on the tram wheel-rail interface condition. The methodology relies on the following measurements: tram failure log-files regarding wheel-sliding events, monitored acoustics data and open source weather information. The proposed methodology consists of three stages: 1) data collection and pre-processing, 2) spatial analysis based on clustering, and 3) decision support based on the extracted information. For clustering, the Density-Based Algorithm (DBSCAN) is used for the analysis of wheel-sliding events. Self-organizing maps (SOMs) are employed for the analysis of acoustics data. A real-life case study is used to show how use of the methodology can find interesting hotspots that are candidates for further monitoring and maintenance actions. The measurements were obtained from the tram system in the city of Rotterdam, The Netherlands.

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Keywords: Decision support systems; wheel-rail interface; tram infra maintenance; self-organizing maps; density-based clustering.

1. INTRODUCTION

In the literature, a tram is usually included in the wider term “light rail transit” (Hensher, 2016; Love et al., 2017). Tram systems are embedded in cities and urban areas (Shi et al., 2017; Zhao et al., 2018). Over time, tram traffic and various exogenous variables cause the natural deterioration of the whole tram infrastructure (Oregui et al., 2017). Without an adequate tram asset management strategy, safety and the good structural health condition of the tram system cannot be guaranteed by the infrastructure manager (Talbot, 2013; Wu et al., 2018). Unexpected faults and accidents might have a strong impact on the users, affecting travel time, safety, and the operation of other transportation modes in the city. Because of all the interactions with other modes of transportation and the environment, the tram system should be analyzed as a whole, with integrated tram asset management strategies.

One approach to improve tram infrastructure performance is to implement efficient health condition monitoring systems that can provide actual information to decision support tools (Kouroussis et al., 2017). Decision support systems provide systematic methods to ease the selection of problem-solving strategies in complex environments (Information Builders, 2017; Jamshidi et al., 2017). In the literature, different decision support systems have been applied in various fields (Marcomini et al., 2008).

In the case of tram systems, the design of decision support systems that rely on conditioning monitoring faces three main challenges. First, the volume of measured data originating from the tram system is large and continues to grow with every new measurement. The increasing number of tram vehicles, the accessibility of new modern monitoring systems, and the desire to implement continuous monitoring of the wheel-rail interface are the three factors that highlight the importance of new methodologies that can automatically handle large datasets. Second, tram data are affected by different disturbances and sources of noise. For example, when a tram is running in an urban area, tunnels or surrounding buildings could obstruct the GPS signals. In addition, noise and disturbances that might affect the sensors of the monitoring systems inevitably occur. To extract the valuable information from the tram datasets, disturbances and noises must be studied and eliminated when possible. Third, tram datasets are composed of many different types: acoustics, weather, tram failures, video images, and ultrasonics, among others. The integration of the multiple sources of information with different data type is difficult. For example, positioning may not be perfectly matched among diverse datasets.

In this paper, we propose a methodology to make use of the extracted information regarding the tram system and to suggest concrete maintenance actions. In the case of tram systems, few methodologies have been reported in the literature. Relying on measured tram failure logfile and

acoustics data, the proposed methodology can extract information from the large datasets affected by disturbances. We claim that the data collected is valuable, and information can be provided that is conducive to the support of tram asset management decisions.

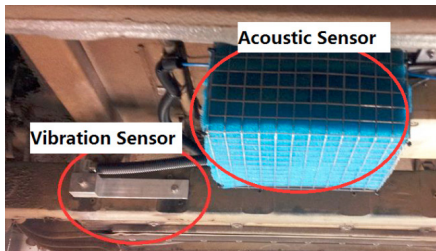
2. METHODOLOGY

The methodology for the design of a decision support tool based on multi-source data analysis for the tram wheel-rail interface is presented in this chapter. Three stages are considered, as described next.

In Stage I, the data source that refers to the condition of the tram and wheel-rail interface for supporting the decision-making process is obtained from sensors mounted on the tram; these data include the tram failure logfile and the monitored acoustics dataset (see Figure 1). The tram failure logfile is considered as an internal dataset originating from the tram itself. Each failure event logs consists of the tram identification serial, the date and the time when the failure occurred, the GPS locations where the failure occurred, and other features (such as speed of the tram and type of failure). In this paper, the focus is on the wheel-sliding events. In the case of the monitored acoustics dataset, this is considered an external data set as it is obtained by normal trams equipped with the sensors. The acoustic data is obtained for the whole tram network infrastructure and recording the following: the time of the measurement, GPS location, the speed of the tram, and the 24 relevant frequency bands (dB_32 Hz, ..., dB_6300 Hz).



(a)



(b)

Fig. 1. (a) Tram under maintenance activities, (b) vibration and acoustic sensors mounted under a normal tram.

Besides, in Stage 1, other information is collected from external sources to support the analysis of both the wheel-sliding dataset and the acoustic dataset: weather condition and the map of the Rotterdam tram infrastructure.

Stage II consists of the data clustering. Before clustering, the location information of the tram track segment is generated with the information of the map of Rotterdam.

Next, to analyze the temporal features of tram wheel-sliding failure events, heterogeneous temporal data aggregation is performed. For this dataset, the density-based clustering algorithm (DBSCAN) is used to investigate the spatial ‘tram failure hotspots’. It is helpful to describe the collected data when the events occur regarding hours, days, months and years. In this study, the time structures of the hour, the day, the month and the year are inspected, as shown in Figure 2. For temporal analysis, the following phases are considered:

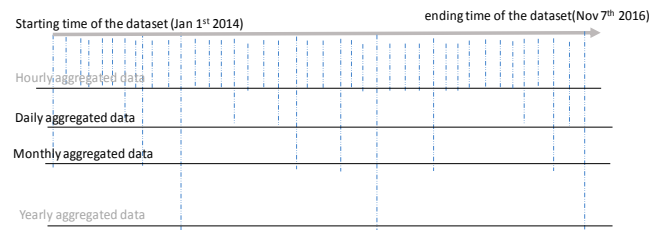


Fig. 2. Heterogeneous temporal data aggregation.

Phase-1: Aggregated data generation. The time series is represented in a manner to compare the number of wheel-sliding failure events between different time slots. Different aggregate levels are considered (hours, days, months, years).

Phase-2: Time slot comparison. After the generation of the aggregated failure event count of the time slots, a comparison among the datasets is performed.

Phase-3: Weather condition information is used to assist the temporal analysis. Along with the previous step, the time slots with large amount of tram failure events are exposed. In this phase, the obtained weather information is involved to gain insights into the failure event distribution over time.

Phase-4: The extracted information is applied to Stage 3 to support the decision making.

To uncover how the segments of infrastructure are associated with the particular tram failure events, the variation of failure event density among the research region must be determined. Hence, this section provides the information of the spatial clustering approach, which includes clustering method selection and clustering parameter determination.

Spatial analysis is performed according to the following iterative procedure:

Phase-1: Generate tram-track data with map development.

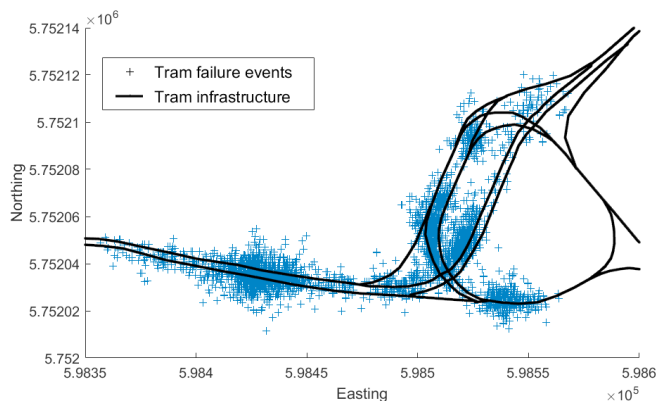
Phase-2: Set the parameter ‘Eps’ (radius of the cluster) with the evaluated GPS disturbance and initialize the parameter ‘MinPts’ (minimum points required inside the cluster).

Phase-3: Run the DBSCAN and validate the output. If the output is satisfied, then go to Phase-5; otherwise go to Phase-4.

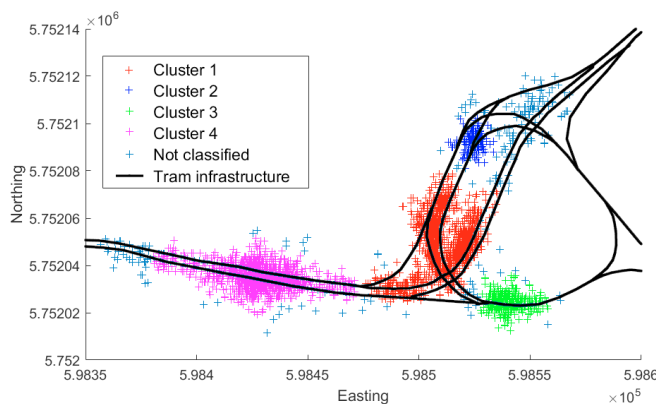
Phase-4: Update the parameters Eps and MinPts and return to Phase-3.

Phase-5: The extracted information will be applied to Stage 3 for decision support.

Figure 4a shows an example of wheel-sliding data for a segment in the tram infrastructure. Figure 4b shows an example of the results obtained based on DBSCAN algorithm to the wheel-sliding event dataset. Note that the GPS data of the obtained tram failure logfile is disturbed by noise, resulting in the scattered data around the track. From the results, the clusters are related with spots/locations with events that occurred near to each other. The different color crosses are the detected clusters, and the black crosses are recognized as spare dots and do not belong to any clusters.



a) Illustration tram failure events and GPS location. Data before performing DBSCAN.



b) Failure events and GPS locations. Data after performing DBSCAN.

Fig. 3. Wheel-sliding data, spatial analysis with DBSCAN.

In the case of acoustics, a self-organizing map (SOM) is used for clustering responses that are similar to each other. SOM is suitable to determine the distribution of an input over a lower dimensional output (Ultsch, 1990; Kohonen, 1990, 2013). This facilitate visualization of complex data and further

analysis of its similarities (Llanos et al., 2017). An SOM consists of neurons organized on a regular low-dimensional grid. The number of neurons may vary according to the complexity of the data. The neurons are connected to adjacent neurons by a neighborhood relation, which dictates the topology of the map. There exist many versions of the SOM. The basic SOM defines a mapping from the input data space onto a regular two-dimensional array of nodes; this SOM will be implemented in this study. The self-organization process involves four major components (Bullinaria, 2004):

- Initialization: All the connection weights are initialized with small random values.
- Competition: For each input pattern, the neurons compute their respective values of a discriminant function, which provides the basis for competition. The neuron with the smallest value of the discriminant function is declared the winner. There is only one winner (output neuron) for one input neuron.
- Cooperation: The winning neuron determines the spatial location of a topological neighborhood of excited neurons, thereby providing the basis for cooperation among neighboring neurons.
- Adaptation: The excited neurons decrease their values of the discriminant function regarding the input pattern through suitable adjustment of the associated connection weights, such that the response of the winning neuron to the subsequent application of a similar input pattern is enhanced.

To implement the self-organizing map algorithm, the SOM toolbox in MATLAB-R2106 is employed. The implementation phases are given below, with an example shown in Figure 4.

Phase-1: Use SOM toolbox to perform clustering on the obtained high-dimensional signal data to obtain a two-dimensional projection plot. Five basic steps of SOM are given according to (Kangas & Kohonen, 1996).

Phase-2: Examine the reliability of the detected clusters of the physical response data regarding the tram wheel-rail interface, e.g., perform speed comparison among the clusters.

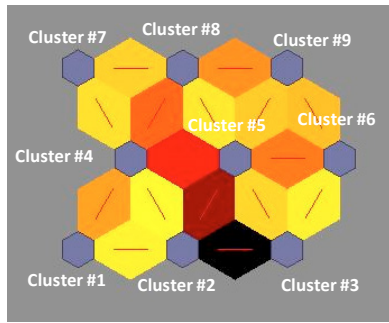
Phase-3: Spatial analysis of the detected clusters. Determine the association between the locations and the detected clusters.

Phase-4: The extracted information are integrated with those from internal dataset and applied to Stage 3 to support the decision making.

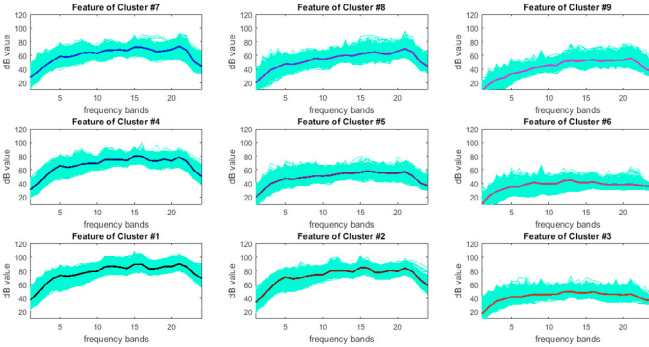
As shown in Figure 4a, as the shapes of the nodes are hexagons, each of the neurons could maximally connect with 6 other neurons. Taking Cluster #5 as an example, Cluster #2, Cluster #3, Cluster #4, Cluster #6, Cluster #7, and Cluster #8 are the 1-neighborhoods. As the information delivered by different colors of the rhombuses, Cluster #8 is most similar with Cluster #5 among all the 1-neighborhoods, as is also

proved by the signal feature plots in the right sub-figure. Among all the 1-neighborhoods, Cluster #2 and Cluster #3 have the greatest dissimilarity, as also shown by the dark rhombus in the left sub-figure. This can be observed from the data belonging to each cluster in Figure 4b.

Finally, in Stage III, the extracted information is applied as decision support in the commercial context. As the physical properties of most of the signals are still the subject of further field validation and research, for this tram maintenance decision support, the decision generated is limited to identify where the most interesting areas are located. Thus, different priorities could be defined for the monitoring and maintenance of these locations.



a) Topological grid output



b) Signal feature of the grouped clusters of the 3 by 3 SOM

Fig. 4. A 3 by 3 SOM example.

3. CASE STUDY

The case study of the city of Rotterdam in The Netherlands is used to discuss the methodology.

In the first stage, the internal data was based on the tram failure event logfile provided by RET (internal dataset), and the external data is the monitored acoustics data obtained by Sensornet (external dataset).

In the second stage, for the internal data analysis, from the temporal perspective, autumn was identified as the wheel-sliding season. Figure 5 shows an example of the daily aggregated visualization of the wheel-sliding event counts of the year of 2015. From Figure 5, it is obvious that October and November (as two months of autumn) have more wheel-sliding events than the rest of the months.

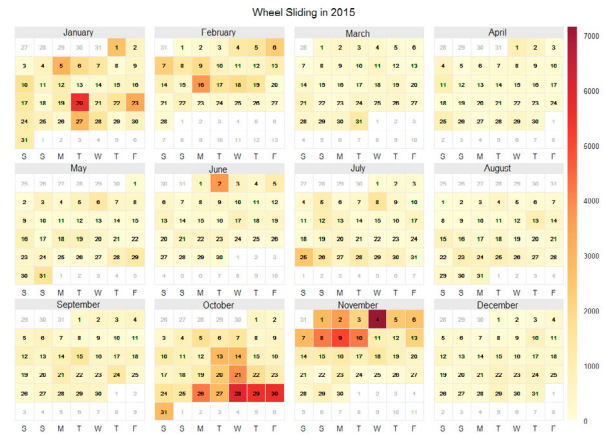


Fig. 5 Calendar plot of the wheel-sliding event counts.

The autumn railway wheel-sliding issue (as a result of leaf contamination) has been investigated by several studies. First, leaf contamination has been identified as the primary cause of low adhesion incidents occurring on some railway networks in the last few decades (Arias-Cuevas et al., 2010), and the loss of adhesion between railroad wheel and the track has implications for both braking and traction. Second, leaf-contaminated contact was found to lead to low adhesion under both dry and wet conditions (Arias-Cuevas et al., 2008). Third, wet leaves were found to lead to a lower traction coefficient value (Zhu et al., 2014) and a lower minimum adhesion coefficient than under dry leave conditions (Arias-Cuevas & Li, 2011). In the natural environment, the wet leaves situation could be a result of leaves falling onto the line in the damp weather, followed by the rolling action of the passing wheels compressing them.

For this case study, to further investigate the effect of the condition and the variation of weather to the occurrence of wheel-sliding events, the weather information is obtained from an external source. Based on weather data from 2014, 2015 and 2016, it was found that wheel-sliding events in the autumn are highly related with high wind speed, and humidity, possibly leading to the fallen-leaf issue.

The high wheel-sliding incidence locations were analyzed spatially using the density clustering algorithm (DBSCAN). Next, four 'hotspots' locations were distinguished among the 100 detected 'wheel-sliding' spots (see Figure 6).

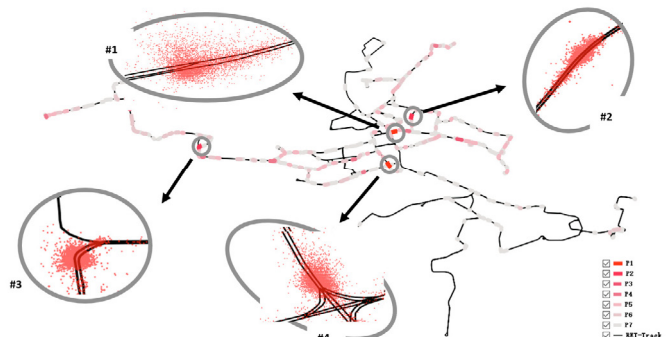


Fig. 6 Detected wheel-sliding locations.

Third, monitored acoustics data are used to estimate the track health condition. Self-organizing map (SOM) was employed to classify the different acoustics responses into the different groups (see Figure 7). After tuning, a grid of 10×10 clusters was considered. For the external data analysis, by differentiating monitoring acoustics data into groups, four hotspots were detected in two special groups of the physical response. The two groups of the acoustics data exposed the crossings and sharp curves and the particular segments in the city center, respectively.

Spatial analysis was performed on two groups of acoustical observations. One group, Cluster #95, is in Rotterdam Central, with three important wheel-sliding spots, see Figure 8. The other group, Cluster #10, is related to crossings and sharp curves in the infrastructure, see Figure 9.

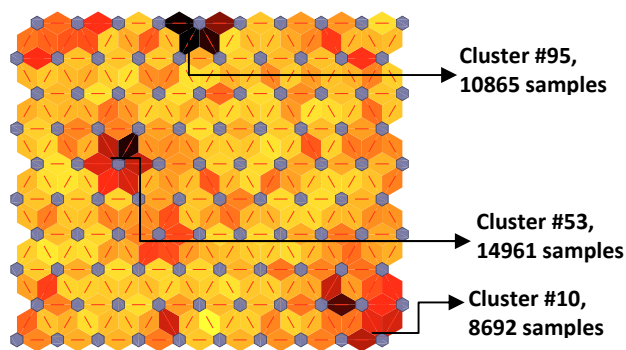


Fig. 7 SOM projection of the acoustical data.

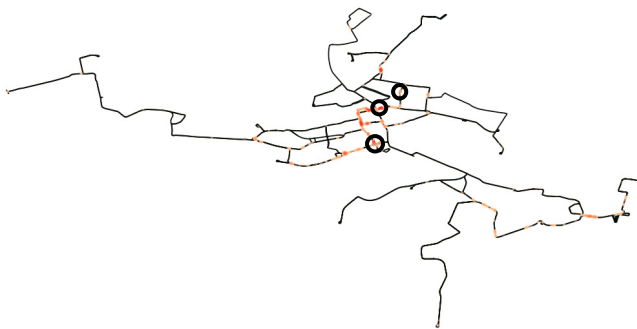


Fig. 8 Spatial visualization of Cluster #95.

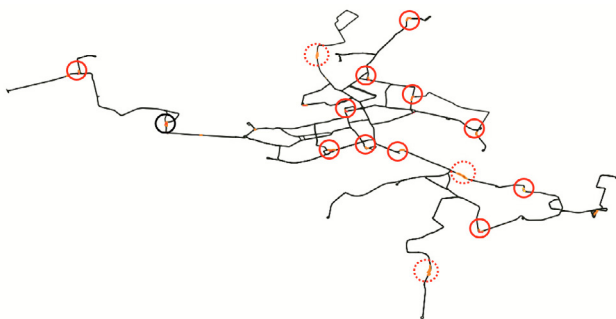


Fig. 9 Spatial visualization of Cluster #10. Circles with solid line indicate sharp curves, circles with dashed-line are members of Cluster #10 but are not sharp curves.

In the third stage, the uncovered facts from the previous two stages were used to support the decision-making process. From the seasonal perspective, the tram wheel-sliding events typically become intensified in winter and autumn. Moreover, from the spatial perspective, one hundred wheel-sliding spots were found. Weather indicators were uncovered as the factors that are highly associated with wheel-sliding events, especially in autumn. Four track spots were found to face a more severe wheel-sliding issue than the rest of the track segments. The common features of those four spots, such as sharp curve, nearby trees, and land slope, were determined.

Hence, the information assists in making subsequent actions more intelligently. To minimize the number of occurrences of wheel-sliding events in the future and to avoid further track default, seasonal actions and location-related actions should be consistently taken by the tram operator.

4. CONCLUSIONS

New decision support approaches embedded into well-designed tram asset management systems can have a great impact on their operations. This study proposed a methodology to facilitate the decision-making process during the development of the maintenance strategy regarding the tram wheel-rail interface. Using this methodology, spatial localization of interesting spots is systematically obtained and suggestions for maintenance operations based on the condition data are provided. Moreover, with the developed and implemented model with the use of different data sources, the results of the study match the forecasted issues related to the natural environment, e.g., the seasonal wheel-sliding issues and the on-spot investigation of the detected four severe wheel-sliding locations.

In the case study, 100 wheel-sliding spots were found, with 4 having more severe wheel-sliding events. The common features of the 4 locations are: 1) trees are found along the track, 2) a slight land slope, and 3) sharp curves in the infrastructure. From the temporal perspective, autumn and winter were determined as wheel-sliding seasons and were found to be highly associated with temperature, wind speed, and humidity. By differentiating monitoring acoustics data into groups, two special groups of the physical response were found to be related to the detected four hotspots. Maintenance suggestions were provided to tram company as decision support regarding the spatial perspective and the temporal perspective.

As part of the further research, the methodology could be applied to other tram networks in different cities and could be extended for use in the analysis of other railway systems. A better interpretation of the field observations and the physical meaning of the responses are also topics for further research.

ACKNOWLEDGEMENTS

The authors appreciate the support of RET (the tram operation and maintenance sector) and Sensornet (an environmental monitoring company) for providing the data used in this study.

REFERENCES

- Arias-Cuevas, O., Li, Z., Lewis, R., & Gallardo Hernandez, A. (2008). Rolling-sliding laboratory tests of friction modifiers in leaf contaminated wheel-rail contacts. In STLE/ASME 2008 International Joint Tribology Conference (pp. 213-215). American Society of Mechanical Engineers.
- Arias-Cuevas, & Li. (2011). Field investigations into the adhesion recovery in leaf-contaminated wheel-rail contacts with locomotive sanders. Proceedings of the Institution of Mechanical Engineers, Part F: Journal of Rail and Rapid Transit, 225(5), 443-456.
- Arias-Cuevas, O., Li, Z., Lewis, R., & Gallardo-Hernandez, E. A. (2010). Laboratory investigation of some sanding parameters to improve the adhesion in leaf-contaminated wheel—rail contacts. Proceedings of the Institution of Mechanical Engineers, Part F: Journal of Rail and Rapid Transit, 224(3), 139-157.
- Aronson, J. E., Liang, T. P., & Turban, E. (2005). Decision support systems and intelligent systems. Pearson Prentice-Hall.
- Bullinaria, J. A. (2004). Self Organizing Maps: Fundamentals.
- Hensher, D. (2016). “Why is light rail starting to dominate bus rapid transit yet again?”. Transport Reviews, 36(3), 289-292.
- Jamshidi, A., Faghih-Roohi, S., Hajizadeh, S., Núñez, A., Babuška, R., Dollevoet, R., Li, Z. and De Schutter, B. (2017). A big data analysis approach for rail failure risk assessment. Risk Analysis, 37(8), 1495-1507.
- Kangas, J., & Kohonen, T. (1996). Developments and applications of the self-organizing map and related algorithms. Mathematics and Computers in Simulation, 41(1-2), 3-12.
- Kohonen, T. (1990). The self-organizing map. Proceedings of the IEEE, 78(9), 1464-1480.
- Kohonen, T. (2013). Essentials of the self-organizing map. Neural Networks, 37, 52-65.
- Kouroussis, G., Vogiatzis, K., & Connolly, D.P. (2017). Assessment of railway ground vibration in urban area using in-situ transfer mobilities and simulated vehicle-track interaction. International Journal of Rail Transportation, 6(2), 113-130.
- Llanos, J., Morales, R., Núñez, A., Sáez, D., Lacalle, M., Marin, L.G., Hernandez, R., & Lanas, F. (2017). Load estimation for microgrid planning based on a self-organizing map methodology. Applied Soft Computing, 53, 323-335.
- Love, P., Ahiaga-Dagbui, D., Welde, M., & Odeck, J. (2017). Light rail transit cost performance: Opportunities for future-proofing. Transportation Research Part A: Policy and Practice, 100(2017), 27-39.
- Marcomini, A., Suter, G.W., & Critto, A. (2008). Decision support systems for risk-based management of contaminated sites. Springer Science & Business Media, 763.
- MathWorks. (2017). Cluster with Self-Organizing Map Neural Network. Retrieved from MathWorks: <https://nl.mathworks.com/help/nnet/ug/cluster-with-self-organizing-map-neural-network.html>
- Oregui, M., Li, S., Núñez, A., Li, Z., Carroll, R., and Dollevoet, R. (2017). Monitoring bolt tightness of rail joints using axle box acceleration measurements. Structural Control and Health Monitoring, 24:e1848.
- Power, D. (2002). Decision support systems: concepts and resources for managers. Westport: Conn., Quorum Books.
- Shi, J., Sun, Y., Schonfeld, P., & Qi, J. (2017). Joint optimization of tram timetables and signal timing adjustments at intersections. Transportation Research Part C: Emerging Technologies, 83, 104-119.
- SOM implementation in SOM Toolbox. (2005). Retrieved from Aalto University: <http://www.cis.hut.fi/projects/somtoolbox/documentation/somalg.shtml>
- Talbot, J. (2014). Lift-over crossings as a solution to tram-generated ground-borne vibration and re-radiated noise. Proceedings of the Institution of Mechanical Engineers, Part F: Journal of Rail and Rapid Transit, 228(8), 878 – 886.
- Ulsch, A. (1990). Kohonen's self organizing feature maps for exploratory data analysis. International Neural Network Conference, pp. 305-308.
- Wu, C., Qiang, X., Wang, Y., Yan, C., & Zhai, G. (2018). Efficient detection of obstacles on tramways using adaptive multilevel thresholding and region growing methods. Proceedings of the Institution of Mechanical Engineers, Part F: Journal of Rail and Rapid Transit, in press. DOI: 10.1177/0954409717720840
- Zhao, X., Li, Y., Xu, S., & Zhai, H (2018). Modeling a modern tram system integrated with a road traffic simulation. Simulation, 94(1), 77 – 90.
- Zhu, Y., Olofsson, U., & Nilsson, R. (2014). A field test study of leaf contamination on railhead surfaces. Proceedings of the Institution of Mechanical Engineers, Part F: Journal of Rail and Rapid Transit, 228(1), 71-84.