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A Framework for Selecting Data Acquisition Technology in Support of Railway Infrastructure Predictive Maintenance

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Abstract

The maintenance of railway infrastructure remains a challenge. Data acquisition technologies have evolved because of Industry 4.0, expanding the capabilities of predictive maintenance. Despite the advances, the potential of these emerging technologies has not been fully realised. This paper presents a technology selection framework in support of railway infrastructure predictive maintenance, which is based on qualitative methods. It consists of three stages, including the mapping of the infrastructure characteristics with the identified technologies, the evaluation of the most appropriate technologies, and the sourcing thereof. This presents the collective decision support output of the framework.

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Keywords: Railway Infrastructure; Predictive Maintenance; Data Acquisition Technology; Technology Selection Framework

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1. Introduction

Advancements in technology are responsible for driving organisations in various industries to change and adapt their current operations to remain competitive. This is seen through the evolution of maintenance practices. With the current maintenance generation adopted due to safety-orientated approaches by maintenance practitioners [1]. One maintenance strategy that can benefit from utilising the advanced technologies is predictive maintenance. To implement such a strategy, it requires regular inspection and monitoring which can be achieved through the help of emerging technologies. However, the amount of specialised knowledge and equipment required for such an approach is moderate to extensive. That being said the cost of maintenance and corrective action are minimal [2]. Part of the technological advancements are that the cost of digital technologies has reduced, and these have become more widely available. Coupled with the growth of the digital supply network, it sets the stage for predictive maintenance to be implemented across various industries [3].

The railway sector is one such industry that can benefit from the adoption and implementation of emerging technologies for condition monitoring of their assets in support of predictive maintenance. However, against the background of railway infrastructure maintenance, the problem is that maintenance

Nomenclature

AHP	Analytical Hierarch Process
DAQ	Data Acquisition
DAS	Data Acquisition System
MCDA	Multi-Criteria Decision Analysis
ICT	Information and Communication Technology
RITSS	Railway Infrastructure Technology Selection Support
UAV	Unmanned Arial Vehicle

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managers have not leveraged the full potential of emerging data acquisition (DAQ) technologies to support a predictive maintenance approach. This problem is attributed largely to uncertainty based on technological capabilities, challenges throughout the process from identification to sourcing of the technology, and the potential benefits associated with the adoption of a technology. A DAQ technology system is defined as the sensors, actors, and operational data acquisition system, which interprets physical factors into signals. These are converted through signal conditioning into analogue and digital functions. The functions provide output measurements, which are interpreted by a sensing control module and used to feedback and control the actuators of the physical process [4,5].

As mentioned already, technological advancements are a driving force behind companies for staying competitive. One way of keeping up with the rapid changes is technology acquisitions, but this also poses another problem for organisations. Organisations are concerned with two acquisition aspects; the first is, what technology to acquire and secondly how to acquire the identified technology [4,5]. Thus, organisations can benefit from a framework that provides them with decision support ranging from the identification and selection of suitable emerging technologies to the sourcing strategy. The technology selection framework described in this paper includes the following three stages:

- Stage 1 – Mapping the emerging data acquisition technologies to the asset in question, to identify suitable technologies that can meet the organisation's needs.
- Stage 2 – Evaluating the candidate technologies against multiple criteria, which reflect the organisation's needs, to select the technology that is best suited for the organisation.
- Stage 3 – Providing decision support for organisations as to what method of acquiring/sourcing the shortlisted technology is preferable according to an organisation's requirements and capabilities. Consider whether to manufacture the technology, acquire the technology from a third party or to cooperate with a third party to establish the technology.

This paper presents the Railway Infrastructure Technology Selection Support (RITSS) framework as a means of selecting emerging DAQ technologies in support of railway infrastructure predictive maintenance. This is seen as a strategy for initiating or progressing railway organisations' predictive maintenance efforts towards a more autonomous and digital approach. Railway infrastructure maintenance condition monitoring technologies are presented, followed by the framework development, the framework methodology, its validation by testing its real-world applicability. The paper ends with a conclusion and recommendations for future research.

2. Railway infrastructure condition monitoring

Similar to other industries, railway maintenance technologies have undergone extensive developments in the condition monitoring field. These developments entail the technologies becoming more digitised and more automated, along with an increase in their capabilities and a reduction in the cost of the technology itself [8,9]. Improvement opportunities include: the reduction of the human inspection requirements and the overall maintenance through early fault detection and prediction [8]; automated real-time data acquisition for quality monitoring [10]; and condition monitoring through computational intelligence methods [11]. However, within the rail industry key enabling technologies are required to apply a desired infrastructure maintenance approach. This approach should incorporate the following characteristics: (i) real-time DAQ, (ii) analysis and processing, and (iii) decision-making activities. The key enabling technologies together form the data acquisition system (DAS) which can be subdivided into two distinct categories, namely the DAQ technologies and the information and communication technologies (ICTs) (Fig. 1).

The DAQ technologies include the devices and sensors capable of acquiring the condition monitoring data [4,8], and the ICTs are responsible for transmitting the data, storing of the data, data processing and analysis, and the monitoring devices which acts as the operator interface. Data transmission is either wired or wireless from the DAQ technology to a cloud server consisting of hardware, networks, storage, services, and

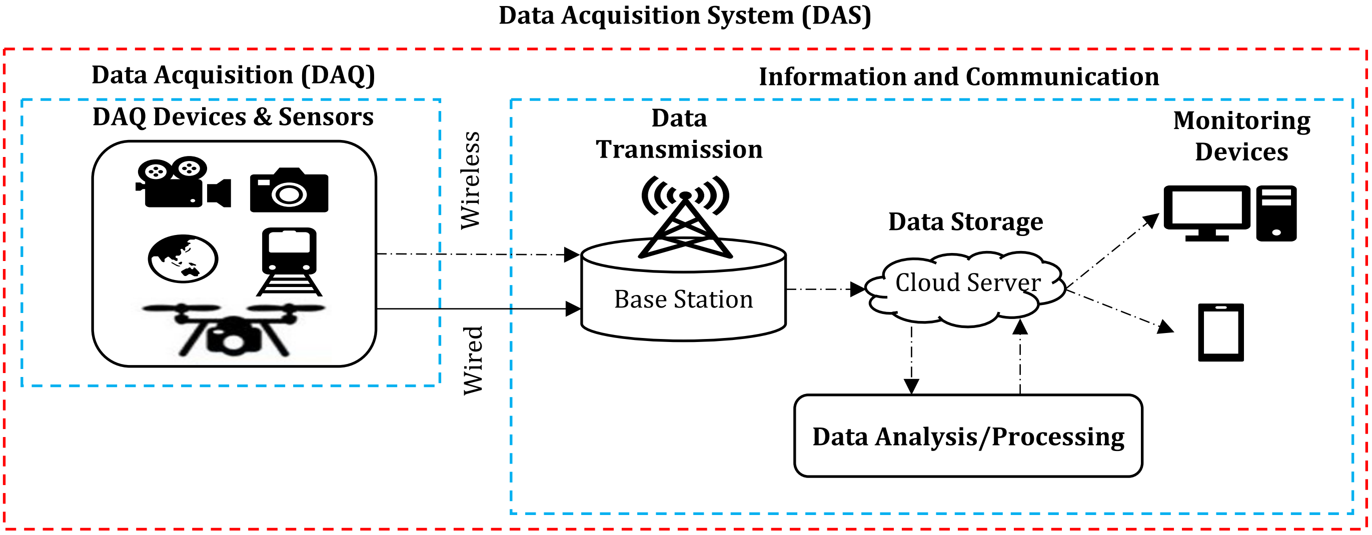

Fig. 1. Data acquisition system

interfaces enabling the delivery of computing as a service. This allows for real-time analysis and processing, which consist of software that can interpret big data sets and providing suggested actions. Monitoring devices enable interaction with the information stored in the cloud server environment. Currently, the DAQ technologies used in railway maintenance for condition monitoring are extensive with numerous sensors and capabilities, but the vast majority still lack the utilisation of advanced ICTs to realise the full potential of a desired DAS [8,12]. This paper presents the selection of DAQ technologies as an initiating step towards a predictive maintenance approach.

3. Framework development

The research followed a *mixed-method exploratory sequential design* [13]. The methodology incorporated both quantitative and qualitative aspects with the qualitative part being dominant. The study consisted of two phases, the first phase being responsible for contextualising the problem and the second phase for the framework development.

The development of the framework incorporated inputs from various sources that are integrated to present the final framework. The sources can be categorised as literature, a panel of international subject matter experts, and industry practitioners/professionals. The international subject matter experts included in the study possess expertise in the railway maintenance sector and come from different backgrounds such as academic researchers, independent consultants, and employees of railway operators. The expert panel had representation from Austria, the Netherlands, South Africa, and Slovakia. The industry practitioners included only participants who work for a railway operator in a managerial or decision-making position.

The framework development is constructed upon the contextualisation foundation, which consisted of an extensive literature analysis of railway infrastructure maintenance and the DAQ technologies used for condition monitoring. Also, a survey incorporating the international industry subject matter experts is used to explore technology adoption in the railway maintenance environment. This survey is used to develop the evaluation criteria (Section 4.2).

As for the framework development methodology, it is initiated by the construction of a set of design requirements the framework must adhere to. These requirements are constructed and adjusted accordingly through an iterative process. Following the design requirements, a structured review is conducted to identify multiple technology selection frameworks. These existing selection frameworks are then evaluated against the design requirements and from this it is found that none of the frameworks met all the requirements and as such justified the creation of the RITSS framework. However, certain aspects of the existing framework analysis are incorporated into the RITSS framework. All the existing frameworks analysed incorporated some form of multiple-criteria decision analysis (MCDA) technique to evaluate the candidate technologies against a set of criteria. From this finding, the technique used in the RITSS framework is chosen, which is a combination of the analytical hierarchy process (AHP) and the criterion-weighted sum method [4,12]. Once the technique is defined, the criteria are developed from the data gathered during the first-round survey. The last step before the integration is to explore different methods for aiding organisations in selecting an appropriate acquisition strategy or mode.

4. RITSS Framework

The Railway Infrastructure Technology Selection Support (RITSS) framework is developed to support railway operators with the process of identifying, selecting, and acquiring emerging DAQ technologies. The three stages of the RITSS framework, as mentioned in the introduction, is further described in this section. Fig. 2, graphically depicts the RITSS framework methodology.

4.1. Stage 1 – Mapping technology to asset

This stage is responsible for creating the link between the assets the organisation wants to address and the emerging DAQ technologies capable of acquiring condition monitoring data. This mapping is critical, as condition monitoring technology is only effective and provides benefit to an organisation, if the technology is capable of reporting on certain relevant indicators associated with the performance of an asset [14].

The first step is to define the asset scope, which entails determining its functionality, the respective failure modes, and associated monitoring parameters of an asset. This helps to narrow the scope of technologies that require identification. For this study the following railway infrastructure components are included: rail track (rails, sleepers, ballast), formation (sub-ballast, subgrade), surface drains, overhead traction equipment,

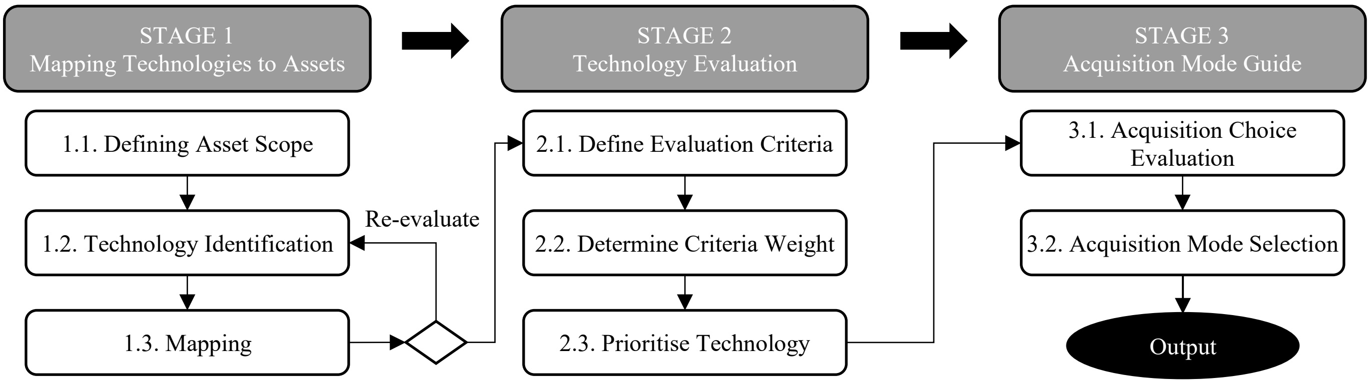

Fig. 2. RITSS Framework

and signalling. The second step is to identify the emerging technologies according to their applicability for performing condition monitoring of the assets as defined by the scope. This can be achieved, but not limited, through the following methods: literature reviews, advising industry professionals, and scanning for providers [6,7]. As part of the identification process it is important to highlight the monitoring capabilities and the different means of implementing the technologies. In the case of this study, it is found that the DAQ technologies can be attached to different carriers that are able to supplement and even enhance the DAQ technology's capabilities. These carriers are represented as in-service trains, designated rail inspection vehicles/trains, custom railway measuring trolleys, and unmanned aerial vehicles (UAVs) "drones". As for the DAQ technologies 26 different DAQ technologies are included in the final study, e.g., ultrasound, eddy current, inertial measuring units.

The last step of Stage 1 is to combine and map the assets and technologies. This is performed by creating "failure pathways" as described by Davis [7]. A failure pathway is a method of linking the different failure modes and monitoring parameters in a sequence that leads to a catastrophic failure. The failure pathway thus can show the different failure modes and monitoring parameters and their inter-dependencies in a simplistic manner. Once the failure pathway is constructed the DAQ technologies are incorporated by assigning the technologies to the monitoring parameters they can monitor. Given the technology infused failure pathways it is possible to determine if all the necessary parameters are being addressed by the technologies. If that is not the case, the organisation can re-evaluated their candidate technologies and go back to the previous step. Fig. 3, represents an example failure pathway showing the failure mode (F), monitoring parameters (MP) and technology ID (T1,2, etc.).

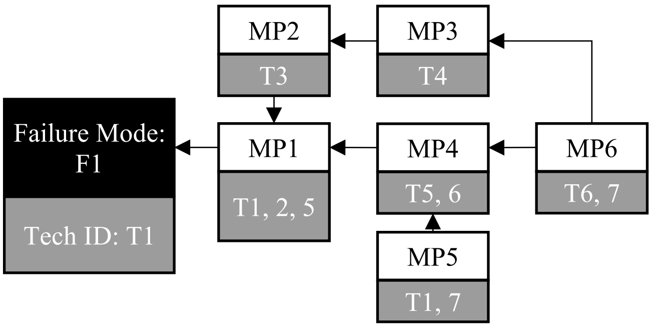

Fig. 3. Example of a failure pathway

4.2. Stage 2 – Technology evaluation

In this stage the candidate technologies are evaluated against a set of criteria to select the most suitable ones for further explorations. Evaluation of the candidate technologies is critical to the selection of the most favourable technologies, as it creates the platform for integrating multiple streams of information in a manner that is structured and logical, ensuring the complex problem is fully addressed.

The first step is to define the evaluation criteria, which entails developing the criteria itself, determining a rating scale (means of assigning a numerical value to a technology's performance with respect to each criteria), and structure the criteria logically in terms of the evaluation process. The criteria are developed predominately from the feedback obtained during the survey to the subject matter experts and supplemented by the literature findings, with the criteria aiming to address the cost, benefits, challenges, and risk associated with each candidate technology [6]. This presented 19 different criteria for the evaluation stage. However, due to the vast amount of inputs required by the subject matter experts when applying the AHP technique to determine the criteria weights similar criteria were grouped, which reduced the final number to 13 sub-criteria. These, sub-criteria can further be grouped together under one of four primary criteria that are technical, institutional, social, and other. The technical criteria are related to the capabilities and potential of the technology itself. Institutional criteria reflect the influence experienced by the organisation through the addition of the emerging technology. Social criteria are aimed at the social impact experienced by the stakeholders such as employees, passengers, public, etc. And the other criteria include miscellaneous aspects. The advantage of utilising AHP is that it allows for both quantitative and qualitative criteria to be used. The challenge with using qualitative criteria is the difficulty in expressing it numerically in the form of a performance score. Thus, a criteria rating scale is developed for each criterion, where the rating scale assigns a performance score of 1-5 to each technology for each criterion based on the appropriate interval the technology falls under. Once the criteria have been developed it is structured according to the hierarchical nature of the AHP technique. This hierarchy presents the evaluation process in five distinct levels. The first level represents the goal, the second the primary criteria, the third the sub-criteria, the fourth the candidate technologies and the fifth the ranked list of suitable DAQ technologies.

The second step of the evaluation stage is to determine the relative importance of each criteria. This is achieved through pairwise comparisons according to AHP [15,16]. Thus, a second survey is used to gather the pairwise judgements from the same subject matter experts used in the initial survey. This process allows for the transformation of the judgments into quantifiable values, which is then used to calculate the weighted value of each criteria. The RITSS framework aggregates the individual judgments first before calculating the priority score rather than calculating the priority score of each expert's judgments and then aggregate the priority scores. The latter tends to require far more calculations, thus straying away from the practicality as intended by the RITSS framework. The criteria weighted values can be observed in both Table 1 and Table 2. These tables present the weighted values as well as the rankings of each criterion. After the criteria weights are determined, the consistency of the judgments are confirmed. According to Saaty, the consistency of the judgments can be determined by calculating the consistency ratio (CR) [15,16]. The CR is calculated (Eq. 1) by dividing the consistency index (CI) by the random index (RI):

$$CR = \frac{CI}{RI} \tag{1}$$

where, the CI is calculated (Eq. 2) with the number of criteria, n, and, λ_{max}, the sum of the vector obtained from multiplying the pairwise matrix by the criteria weighted matrix.

$$CI = \frac{\lambda_{max} - n}{n-1} \qquad (2)$$

The RI, created by Saaty, assigns a specific value according to the number of criteria being considered, e.g. n =1, 2 → RI = 0; n = 4 → RI = 0.9; n = 5 → RI = 1.12.

Table 1: Primary criteria weighted values

CR	Criterion	Weight Value	Rank
1	Technical	0.490	1
2	Institutional	0.177	3
3	Social	0.268	2
4	Other	0.065	4

Table 2: Sub-criteria weighted values

CR	Sub-criterion	Normalised (Rank)	Global (Rank)
1.1	Accuracy	0.275 (2)	0.135 (3)
1.2	Cost	0.053 (5)	0.026 (11)
1.3	Ext. factor influence	0.179 (3)	0.088 (4)
1.4	Cont. monitoring	0.121 (4)	0.059 (6)
1.5	Technology Maturity	0.373 (1)	0.183 (2)
2.1	Traffic interference	0.099 (4)	0.018 (13)
2.2	Early failure prediction	0.421 (1)	0.075 (5)
2.3	Operator skills	0.168 (3)	0.030 (10)
2.4	Security	0.311 (2)	0.055 (7)
3.1	Safety	0.844 (1)	0.226 (1)
3.2	Job uncertainty	0.156 (2)	0.042 (9)
4.1	Environmental	0.304 (2)	0.020 (12)
4.2	Support	0.696 (1)	0.045 (8)

The consistency ratios were calculated for each group of criteria that were judged with respect to each other. Thus, the primary criteria on its own which included technical, institutional, social, and other. The same applied to the sub-criteria that fell under the same primary criteria category, e.g., sub-criteria that falls under the social criteria which is safety and job uncertainty. From the calculations it is evident that the consistency ratios of the primary criteria are 0.099, the technical sub-criteria 0.033, the institutional sub-criteria 0.088, and the social and other sub-criteria 0.00. Thus, all the consistency ratios are < 10% ensuring that the initial judgments are consistent (> 10% indicates inconsistent judgments and requires re-evaluation according to Saaty). Note the CR of 0 for both social and other, which is attributed to the fact that the number of criteria is two and as such must be consistent [15,16].

The final step of the evaluation stage is to prioritise the candidate DAQ technologies from most favourable to least. This is achieved by integrating the DAQ technologies, failure pathways, evaluation criteria, performance scores, and evaluation criteria weights. An extract of the result following the integration is presented in the technology performance score are shown under each criterion (Table 3).

The infrastructure component, trackbed, is seen at the far left, followed by the different DAQ technology identifying codes (IDs) capable of monitoring the trackbed. Furthermore, the technology performance scores are shown under each criterion.

The priority score is calculated by utilising the criterion-weighted sum method and according to the priority score the candidate DAQ technologies are ranked. Thus, presenting the shortlisted DAQ technologies and their respective carrier for condition monitoring of the trackbed. As an example, from Table 3, ground penetrating radar (Tech ID: 10a) accompanied by a designated rail inspection vehicle is determined to be the most suitable DAQ technology combination to monitor the condition of the railway trackbed, followed by "SmartRock" (Tech ID: 22) that is at a fixed location embedded within the ballast rocks.

Table 3: DAQ Technology evaluation and prioritisation

		Evaluation Criteria					
Infra	Tech ID	CR11	CR12	…	CR42	Score	Rank
Trackbed	8	4	2	…	3	3.248	9
	10a	4	1	…	5	4.232	1
	10b	5	2	…	3	3.837	7
	15	3	3	…	3	3.934	5
	21	4	2	…	5	3.791	8
	22	4	3	…	3	4.211	2
	25a	4	3	…	3	4.030	4
	25b	4	1	…	5	4.110	3
	25c	4	2	…	5	3.878	6

4.3. Stage 3 – Acquisition mode guide

In this stage the organisation is provided with decision support as to what method of acquiring the shortlisted DAQ technologies would be most favourable for a particular situation. The guide aims to provide the organisation with advice on whether it is better to *make*, *buy*, or *cooperate,* to acquire a particular technology. In other words, develop the technology in-house, externally source the technology, or a combination of the two. The first step is the acquisition choice evaluation, which evaluates a set of criteria from the perspective of the shortlisted technology and the organisation's needs, goals, and limitations. The choice is made by determining the position of both the DAQ technology and the organisation regarding the four criteria. The four criteria are: resource availability, strategic/technology importance, urgency, and dependency on external organisations. Resource availability is further divided into capital available for the venture/project (high or low) and the research and development (R&D) capabilities (high or low) of the organisation itself. Strategic importance (core or non-core) is a measure of how important the technology is to the organisation's strategy and objectives. Urgency (high or low) is a measure of the timeframe in which the technology must be acquired – whether it is urgently needed or not. Thus, making strategic importance and urgency closely related. The last criterion measures the dependency (high or low) on external organisations for an acquisition mode.

The acquisition mode selection process commences once the organisation's criteria conditions are determined. This selection takes the form of an elimination process where 10 acquisition modes are included from the literature and the conditions under which each mode is favoured. The acquisition modes included are internal R&D, education and training, mergers and acquisitions, direct/embodied acquisitions, R&D contract, consultant, minority investment, licensing, joint venture, and R&D collaboration. By evaluating one criterion at a time an organisation can eliminate the acquisition modes that do not match their criteria condition until only the acquisition mode that matches the organisation's conditions remain. The selection of an appropriate acquisition modes concludes the RITSS framework.

5. RITSS framework validation

The primary goal of the RITSS framework is to serve as decision support for decision-makers working for railway operators when identifying, selecting, and acquiring emerging technologies. The development of the framework followed an iterative approach that allowed for the validation of certain aspects throughout its creation by incorporating sources such as literature and feedback from a panel of international subject matter experts [17]. To validate the RITSS framework in its entirety, face validation according to [17] is performed. This consists of interviews during which the framework is presented, followed by questions to determine whether the framework would be successful in overcoming current challenges, what its strong and weak point are and how it can be improved. Finally, the participants completed a survey of their perception of each of the framework stages (in Fig. 2). Two railway industry practitioners (a management consultant and professional engineer; and an infrastructure maintenance operations manager) are identified for the RITSS framework face validation. Both the participants confirmed the potential of the RITSS framework methodology in the railway industry and the likelihood of its generic application in other industries.

The most notable feedback from the validation is to expand the framework to include not only the DAQ technologies, but also the ICTs which will improve decision making. It was further suggested that the framework be customised and applied to different infrastructure groups of assets (e.g., track, signalling) which will allow for specific decision making for each of the groups. Finally, it was indicated that developing a tool or software that incorporate the RITSS framework methodology would improve its usability.

6. Conclusion

In this paper, the researchers presented the need for railway organisations to make strategic technology acquisitions as a means of staying competitive. The selection of appropriate technologies to acquire, is however not a simple task. The RITSS framework is developed and validated to address this challenge by supporting the selection of emerging DAQ technologies for condition monitoring of railway infrastructure with the idea for shifting towards or improving current predictive maintenance approaches. Recommendations for future research are: to expand the RITSS framework to include information and communication technologies; to customise the generic RITTS framework to cater for different rail infrastructure groups of assets or for a specific organisation; and to explore the application of the RITTS framework outside the rail industry.

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References

[1] N. S. Arunraj and J. Maiti, "Risk-based maintenance-Techniques and applications," *J. Hazard. Mater.*, vol. 142, no. 3, pp. 653–661, 2007.

[2] L. Huang, Y. Chen, S. Chen, and H. Jiang, "Application of RCM analysis based predictive maintenance in nuclear power plants," *Proc. 2012 Int. Conf. Qual. Reliab. Risk, Maintenance, Saf. Eng. ICQR2MSE 2012*, pp. 1015–1021, 2012.

[3] C. Colemen, S. Damodaran, M. Chandramoulin, and E. Deuel, "Making maintenance smarter," *Deloitte Univ. Press*, pp. 1–21, 2017.

[4] W. Kilian, M. Hill, and S. Odenwald, "Adaptive Sensor Data Acquisition for Gait Analysis," *Procedia Eng.*, vol. 147, pp. 659–664, 2016.

[5] H. Fleischmann, J. Kohl and J. Franke, "A modular architecture for the design of condition monitoring processes," *Procedia CIRP*, vol. 57, pp. 410–415, 2016.

[6] D. Ma and S. W. Hung, "An Integrated Framework for the Selection and Acquisition of Core Technologies: The Case of Taiwan's LED Industry," *Long Range Plann.*, vol. 48, no. 6, pp. 381–397, 2015.

[7] P. Davis and J. Brockhurst, "Subsea pipeline infrastructure monitoring: A framework for technology review and selection," *Ocean Eng.*, vol. 104, pp. 540–548, 2015.

[8] V. J. Hodge, S. O'Keefe, M. Weeks, and A. Moulds, "Wireless sensor networks for condition monitoring in the railway industry: A survey," *IEEE Trans. Intell. Transp. Syst.*, vol. 16, no. 3, pp. 1088–1106, 2015.

[9] Y. Qian, M. S. Dersch, Z. Gao, and J. R. Edwards, "Railroad infrastructure 4.0: Development and application of an automatic ballast support condition assessment system," *Transp. Geotech.*, vol. 19, no. July 2018, pp. 19–34, 2019.

[10] M. Miller *et al*, "Development of automated real-time data acquisition system for robotic wel quality monitoring," *Mechatronics*, vol. 12, no. 9-10, pp. 1259–1269, 2002.

[11] T. Żabiński *et al.*, "Condition monitoring in Industry 4.0 production systems - the idea of computational intelligence methods application," *Procedia CIRP.*, vol. 79, pp. 63–67, 2016.

[12] D. Milne *et al.*, "Proving MEMS Technologies for Smarter Railway Infrastructure," *Procedia Eng.*, vol. 143, no. Ictg, pp. 1077–1084, 2016.

[13] J. Creswell and C. Poth, "Designining a Qualitative Study," in *Qualitative Inquiry and Research Design: Choosing Among Five Approaches*, SAGE Publications, 2017, p. 488.

[14] R. W. Saaty, "The analytic hierarchy process-what it is and how it is used," *Math. Model.*, vol. 9, no. 3–5, pp. 161–176, Jan. 1987.

[15] R. D. F. S. M. Russo and R. Camanho, "Criteria in AHP: A systematic review of literature," *Procedia Comput. Sci.*, vol. 55, no. Itqm, pp. 1123–1132, 2015.

[16] P. Davis, E. Sullivan, D. Marlow, and D. Marney, "A selection framework for infrastructure condition monitoring technologies in water and wastewater networks," *Expert Syst. Appl.*, vol. 40, no. 6, pp. 1947–1958, 2013.

[17] D. Borenstein, "Towards a practical method to validate decision support systems," *Decis. Support Syst.*, vol. 23, no. 3, pp. 227–239, 1998.