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Evolution of Decision Support Systems for Railway Infrastructure Managers

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Abstract

Infrastructure maintenance is a complex task due to operational needs of service quality, availability demands, traffic intensity, and budget constraints. Traditionally, maintenance decisions are based on infrastructure managers' experiences, judgments, and available choices. Though, the technology push and the availability of an abundance of data have made an urge to derive the decisions and insights from data. This data-driven approach resulted in computerized solutions, e.g. decision support system (DSS), which are rich in data but poor in insights. The DSS confronted with data management challenges of data acquisitions, data cleaning, and data reliability further complicate the already complex task of maintenance decision-making. To tackle these challenges of maintenance decision-making and data management, a decision-driven approach is suggested for the development of DSS. The decision-driven approach builds on the definition of decision context specified by infrastructure manager. The data requirements are provided by decision context, where the interrelationships between the data and the decision context are made explicit by developing an information model. We illustrate the decision-driven approach for DSS development using a case study of maintenance decisions for bridge selection. It is found that the decision-driven approach directs the focus towards the decision context definition and decision analysis while minimizing the overhead of data management.

Keywords: decision-driven; decision support system; railway assets; maintenance;

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1. Introduction

A railway is a complex and integrated network, where the railway infrastructure and its operations are tightly coupled. A minor failure of an individual element of infrastructure very often leads to operational disruptions, which propagates across the network. According to EuroStat (2016), railway passenger transport performance continues to increase by 6.4 billion passenger-kilometres between 2013 and 2014 (+1.5%). The high utilization of railway operations imposes the large demands of improved service quality. While, on the other hand, the railway infrastructure is exposed to aging and adverse climate change, with approximately 95% of the railway infrastructure being more than 100 years old (European Railway Agency, 2013; European Railway Agency, 2014). Recent major failures such as the collapse in 2009 of the Malahide Viaduct in Ireland due to scour and the failure of Dawlish sea defenses in the UK due to coastal flooding in 2014 are the example of adverse climate or severe weather effects on railway infrastructure. With increasing service demands and aging infrastructure, managers are under a lot of pressure to not only provide a safe operational network, but also to take smart maintenance decisions that improve network availability and prolong the overall service lifetime of infrastructure assets.

Traditionally, the decision to perform maintenance is based on the infrastructure managers' observations, judgments and choices which are derived from available budgets, planned schedules and abrupt failures (Dhillon, 2002). Though, maintenance based on these drivers very often leads to undue maintenance with increased cost. For this reason, predictive maintenance is considered to be a most effective maintenance policy that suggests to perform maintenance only where it is promptly needed (Khan & Haddara, 2003). However, predictive maintenance poses decision-making challenges for infrastructure managers. Particularly, in railways, the maintenance decision-making is a difficult task due to a widespread network of diverse railway objects (e.g. constituting tracks, bridges, switches and crossing, tunnels, electrification system, etc.), availability demands, possession time, deterioration rate and budget constraints. Such infrastructure maintenance requirements pose decision-making dilemmas to the infrastructure managers, where maintenance planning is challenged by the number of conflicting issues (Lidén, 2015). For instance, demand to keep the network available conflicts with increasing rate of deterioration, limited budget vs. aging network, the risk of failures vs. traffic intensity over an object and so on.

These maintenance decision-making dilemmas are difficult to handle based only on experts' choices and on techniques that over-rely on experts' judgments. Therefore, a trend towards the use of the computer-based system, namely decision support system (DSS) is noticed in the last decades. With the availability of economical and efficient IT solutions, an immense amount of data is being collected with the aim to aid in maintenance decision-making process. However, the complexity of collecting data and its management techniques are found to add further difficulty in maintenance decision-making process. With the aim to reduce the complexity of maintenance decision-making and data management overhead, in this paper, a decision-driven approach for the development of DSS is presented. The paper is structured as follows: Section 2 provides the state-of-the-art along with the motivation of decision-driven approach. The design of the decision-driven approach is introduced in Section 3. Section 4 provides an application and illustration of decision-driven approach with the help of a case study. Finally, Section 5 and Section 6 provide the discussion and conclusions, respectively.

2. Point of Departure

Many computerized systems are in use to support infrastructure managers in their daily activities. Decision support systems (DSS) are one of these computerized systems with ever-increasing boundaries to support decision-making, include executive information, visualize geographic information and provide data analytics (Burstein & Holsapple, 2008). The abundance and ease of data collection technologies have led to a desire to support complex decisions with the newly available data (Galar, et al., 2012; Morant, et al., 2014; Nunez, et. al., 2015). The technology push brings the paradigm shift towards the data-driven decision-making. The importance of data-driven decision-making is highlighted immensely in literature. A survey conducted by MIT indicated that the data-driven decision-making has resulted in 4% higher productivity rates and an increase of 6% in profits for the organization (Laskowski, 2011).

A data-driven DSS contributes to the success of an organization, specifically in the manufacturing and merchandising industry, where the demands, supply, and consumer behaviour drive the decisions. However, the domain of railway infrastructure management has dispersed assets, operational demands, segregated nature of the data (e.g. monitoring, services, management), which poses diverse decision-making dilemmas to infrastructure managers. Despite the popularity of DSS, Omar, et. al, (2009) and Labib (2004) mentioned that DSS for railway maintenance is complex and difficult to use, thus provide inadequate support for decision analysis. The limitation of decision analysis capabilities can be traced back to its data-driven development, where much attention is given to data acquisition and data management with the possibility to drive the decision insights.

Recent literature studies on the developments of DSS further validate this trend. Guler (2012) presented a DSS for track maintenance, where an extensive exercise is reported to understand what data is available instead of what data is actually needed. Similarly, a data fusion framework for a number of isolated datasets is proposed for maintenance prognosis and optimal decision-making (Galar et. al., 2012b; Galar et. al., 2012). For the development of intelligent maintenance solutions, Moore & Starr (2006) mentioned the collection of production schedules, condition monitoring data, maintenance records, financial records, safety rules, etc. as a first step. Similarly, the theoretical frameworks proposed for the development of DSS mentioned the data gathering and data analysis as an initial step for DSS development (Agrahari & Tripathi, 2012; Lee et al., 2012).

The unfocused collection of data with the possibility to derive useful decision insights not only leads to delayed and confused decision-making (Appleyard, 2004; Faiz & Edirisinghe, 2009; PAS, 2008), but also poses data reliability challenges. The data collection without the defined framework can result in data, which is incomplete, incorrect and sometimes vulnerable to safety and security of the infrastructure. From the perspective of data storage, information about an infrastructure network is stored in multiple systems categorized based on assets types and operations (see Thaduri et al., (2015)).These data silos possess different data formats and pose diverse protocol requirements for data retrieval. The effort of data retrieval and data cleaning divert the focus of DSS development towards data management instead of providing support in decision making. Though, in the literature related to risk and reliability, a number of decision analysis methods based on Multi-Criteria Decision Analysis (MCDA) are found (De Almeida et al., 2015; Kabir et al., 2014). However, none of above mentioned DSS incorporate MCDA methods for decision support.

With the aim to handle the maintenance decision-making dilemmas and simultaneously minimising data management complexity, a decision-driven approach is introduced in this paper. In a White Paper, issued by SAS (statistical analysis systems), Harris (2016) argues to shift the focus of DSS development from data-driven to decision-driven. The *Decision-driven approach* focuses on the definition of decision context, where the data needs are derived by posed decision questions and decision criteria instead of the other way around (Pera, 2016). Moreover, decision-driven data definition makes the data unavailability and data uncertainly explicit to the infrastructure managers. The proposed decision-driven approach envisions incorporating the methods of MCDA in order to support the maintenance decision-making with explicit data values and subjective judgments of infrastructure managers. We have implemented the Analytical Hierarchy Process (AHP) approach in the decision-support tool described herein. Due to space constraint, a detailed description of the application procedure of AHP can be found at (Allah Bukhsh et al., 2017). In the following section, a design of decision-driven approach for the development of DSS is provided.

3. Design of a decision-driven approach

In this section, a design of decision driven approach for the development of DSS is introduced. The purpose of the presented design is to minimize the data management overhead and stir the development efforts of DSS towards decision-driven approach. The suggested design presents four concrete phases, which are iterative in nature. The detailed steps of each phase are outlined in Figure 1. In the following, details of each phase are outlined briefly.

3.1. Decision Context

The decision context frames the scope of the DSS and provides a base for the implementation of DSS as a computerized tool. In other words, decision context outlines the decisions that must be supported by the DSS. The definition of the decision context requires close collaboration with infrastructure managers in order to understand their decision-making needs as also illustrated in Figure 1. For the specification of decision context, the scope, question(s) and decision criteria must be defined. Decision scope specifies the particular area of infrastructure management that is required to be supported by DSS. The decision scope can be based on assets types; track, bridge, etc. or on assets management domain, e.g. monitoring, operations, management, etc. Such scope definition is solely derived by the infrastructure managers' preferences.

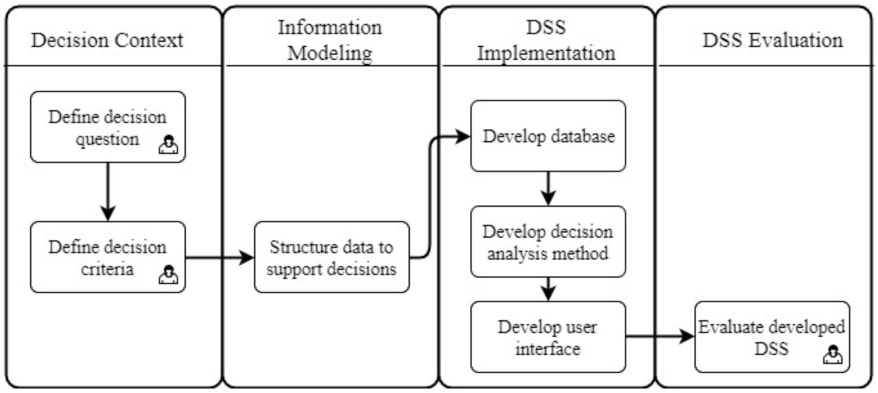

Figure 1: Detailed steps of decision-driven approach

While, *decision question (s)* concretely specifies the decision-making scenarios. For instance, how to minimize the maintenance cost while maximizing the asset reliability. The defined decision question underlines the (conflicting) objectives of decision analysis method in form of minimization and/or maximization of a certain value function. Moreover, a decision question is then quantified by d*ecision criteria*. Keeney (2009) defined the three types of decision criteria, i.e. natural, constructed and proxy. The natural criteria have a common interpretation for all e.g. maintenance cost. While the constructed criteria have to be processed before being used as an attribute for decision analysis method e.g. asset reliability. Proxy criteria are the indirect measure of the decision objective.

The definition of the decision context based on scope, questions and criteria concretely outline the development requirements of DSS from the perspective of required data, tool development, and model decision analysis model implementation.

3.2. Information Modeling

Information modeling has gained a critical importance in structuring and management of large volumes of data having a variety of formats (Leite et al., 2016). For the data collection based on decision context, an information modeling approach is used. An information model clearly outlines the data needs for the decision analysis by defining the objects and their relations. It makes the data structure and objects' relationship explicit for infrastructure managers without involving technical details. The objects of information model correspond to some real or abstract object that might exist in the world or within the state of mind (Kent & Hoberman, 2012; Turk, 2001). Moreover, an information model can also be used as a communication tool. Entity relationship diagrams, class diagrams are intensively used modeling notations to model the information model.

3.3. DSS Implementation

This phase guides the process of DSS development as a computerized tool by following the decision driven approach. A typical DSS has three main components: a database, a decision analysis model and a user interface (Power, 2008).

A *database* provides the data required for decision analysis. In a decision-driven approach, the data structure is defined by an information model. Instead of collecting all the available data, only the data required to support the decision questions are stored in the database. Such decision-driven data collection minimizes the data acquisition and data management overhead considerably. The discussion of technical implementation details e.g. database system, data technology are out of the scope of this study. With the setup of the database, the next step is to define the *decision analysis model*. The decision analysis model provides the main decision logic to DSS. Since each decision model caters to the needs of posed decision context/decision problem, a standard decision analysis model does not exist. The methods of MCDA provide a firm base for the development of decision analysis model, which can be adapted to solve the decision problem at hand. Finally, to enable the data accessibility and to comprehend the results of decision analysis model, an intuitive *user interface* is of utmost importance (Miettinen, 2014). Most of the DSS for infrastructure management requires the GIS support to visualize and locate the infrastructure assets scattered over a network. Considering the involved complexity of decision analysis method, the user interface should be easy to use and allow the infrastructure managers to provide their subjective judgments during decision analysis.

3.4. DSS Evaluation

The last phase is the evaluation of results provided by the decision-driven DSS. In addition to user feedback, the evaluation of the DSS can be performed by manually performing the decision analysis procedures where the final results are compared. Moreover, by executing the decision-analysis procedure manually, the use of data derived from the decision context will be clear, while the unavailable and uncertain data become traceable.

4. Application of decision-driven approach: A case study

This section provides the application of proposed decision-driven approach based on a case study from Irish Railway. The case requires the ranking of railway objects that are in need of maintenance, where the maintenance cost and network downtime is kept at the minimum. The methodology for case setup is provided in Section 4.1. The results and evidence on the usefulness of decision-driven approach for DSS development are outlined in Section 4.2.

4.1. Methodology

To demonstrate the decision-driven development methodology, a prototype of DSS for railway infrastructure network is developed. The developed DSS prototype is part of an ongoing research effort for the Horizon 2020 European project, DESTination Rail, which aims to develop a DSS for the railway infrastructure management (DESTination RAIL, 2015). The phases of decision-driven approach are found to be well aligned with Data-Information-Knowledge-Wisdom (DIKW) hierarchy originated from information science domain (Rowley, 2007). Figure 2 presents the case setup illustrating the decision-driven approach along the lines of DIKW hierarchy.

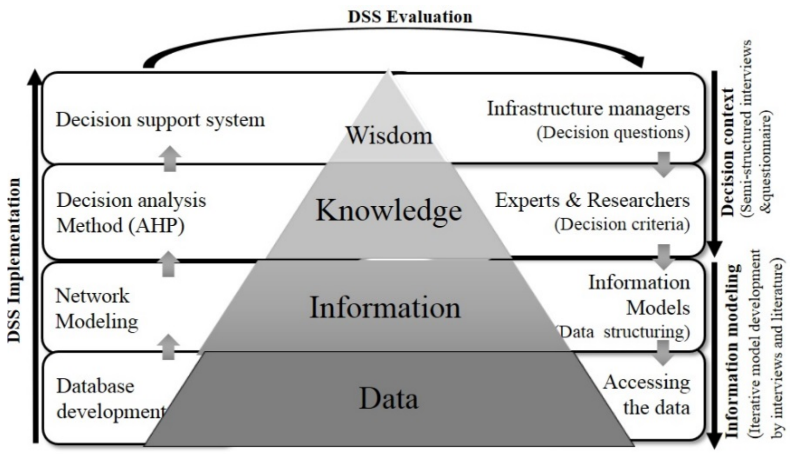

Figure 2: Research activities to demonstrate decision-driven approach with a Case

The decision context is defined based on the implicit *wisdom* of infrastructure managers and explicit knowledge of railway experts and researchers. For this purpose, we organized semi-structured interviews with twelve participants from nine different institutes. The interviewees possess considerable experience of working with asset management systems as well as have practical knowledge of solving problems faced during maintenance planning and optimization. We developed a questionnaire to guide the interview process. The questionnaire consists of questions related to railway infrastructure maintenance. Interviews were conducted over Skype and telephone that lasted between 30 to 60 minutes. These interviews helped us to specify the decision context of the DSS.

Based on the defined decision scope, the efforts of data structuring in the form of information modeling, database development and definition of decision analysis method were initiated. We developed the initial version of the information model by capturing the related concepts and objects that were mentioned during the definition of the decision context. In a second iteration, the initial information model was then enriched with objects' attributes and interrelationship by acquiring knowledge of railway infrastructure maintenance from various other sources, e.g. Esveld (2001) and RailML (Kolmorgen & Huerlimann, 2005). To further improve the information model, again semi-structured interviews were performed with the extended group of experts, who specified the decision context in the beginning. We used the draft information model developed out of the first two iterations to provide an example to the interviewees and to trigger thoughts and critical reviews. The questionnaire was used to ask for the specific data requirements for the decision-making. Overall, the interviews led to numerous comments on the conceptual information model from the second iteration. We used these comments to update the information model concept from the second iteration and to arrive at the final information model. Further details of information models developed for railway infrastructure can be found in (Allah Bukhsh et al., 2015). The developed information model served three purposes, i.e. 1) explicitly defined the data needs 2) provide the concrete framework for the data collection and 3) specify the structure of the database.

Once the data needs were defined within the information model, the next step was to develop the database. The database contains all the data regarding the objects and their attributes that are defined in the information model. The assets' location is provided by Irish Rail for the sake of demonstration only. With the basic data of assets' location, the network models are developed. Considering the decision context defined by infrastructure managers, experts and researchers, a MCDA model is defined. Among the number of methods of MCDA, the analytical hierarchy process (AHP) is chosen due to its simplicity in incorporating objective data and subjective preferences of stakeholders on the ratio scale (Saaty, 2008). For the detailed application procedure of AHP, interested reader can refer to (Allah Bukhsh et al., 2017). Finally, to enable the interaction of infrastructure managers with the decision-driven DSS prototype, a GIS interface is developed. The GIS interface visualizes the railway tracks, stations, bridges, and switches and crossings on the Irish Rail network. These visualizations not only allow the infrastructure managers to locate the objects, but also enable the selection of objects for the maintenance decision analysis. Finally, the evaluation of DSS is performed with three Irish Rail infrastructure managers.

4.2. Case Results

A decision-driven approach streamlined the development of DSS by providing decision context, which is followed by information modeling, implementation, and evaluation. This section provides the results of the case study for maintenance decision analysis.

4.2.1. Decision context

From the number of railway domains such as monitoring, operations, maintenance, timetabling, signaling, interlocking, the maintenance of physical assets (e.g. bridges, tracks, tunnels, slopes) is chosen as a main focus of the DSS. Considering the great number of objects, e.g. Irish Railway has more than 3000 bridges; it was decided to treat the decision problem as a ranking problem, where the most suitable object in terms of maintenance cost and reduced downtime of the network will be selected for maintenance. Based on decision scope problem, the following decision question is formulated; *among the number of objects, which object is under the immediate need of maintenance, while keeping the cost and network downtime minimum?*

To represent decision dilemmas i.e. cost vs. network downtime, four criteria were defined, i.e. maintenance cost, downtime, condition index and train frequency. Maintenance cost, downtime, and train frequency are natural attributes, which are measured in euros, hours and no of trains passing per day respectively. The condition index is a constructed attribute, which is derived from visual inspection and measured with the standard score card of 1-6 where 1 represents the best condition. To illustrate the DSS and implemented decision analysis method, the sample data is used (See Table 1).

4.2.2. Information Model of Railway Objects

Since the decision question does not specify a particular railway object, an information model of relevant railway infrastructure objects outlining the objects' geometry, conditions and locations is provided in Figure 3. To keep the model readable the properties details of few objects are omitted. The presented information model shows the inter-relationships and dependencies of railway objects on one and another). The *track* is the main point of references, which is composed of *Superstructures* and *Substructures*. The *Substructure* of a track can be further detailed into subgrade and drainage. Similarly, *Superstructure* can have zero or more *Structures* and *Switches and Crossings*. A *Superstructure* is composed of *Rail* which is further based on *Sleepers* and *FasteningSystem.* Besides objects' interrelationships, each of the objects has a number of related data parameters. For instance, the track has a unique id, its additional name, a geoCoord for its location tracking and a condition parameter.

The defined decision question also concerns with the need of a maintenance of a particular railway object. Figure 3 (top right) also shows the main object classes for railway maintenance management. Regarding the maintenance of a particular object, a number of important information is required. Most important properties are maintenance type (i.e. *Mtype*), spot history (i.e. *Mhistory*) and imposed speed. The maintenance type can be represented as a renewal, grinding, tamping, or others. Additionally, the information model defines the need of data about all the maintenance activities that have been conducted at a particular section/spot in the past. As maintenance can affect the train operations, it is useful to acquire the data about the imposed speed during the maintenance. The developed information model can be updated as the need of further data emerges depending on the decision context.

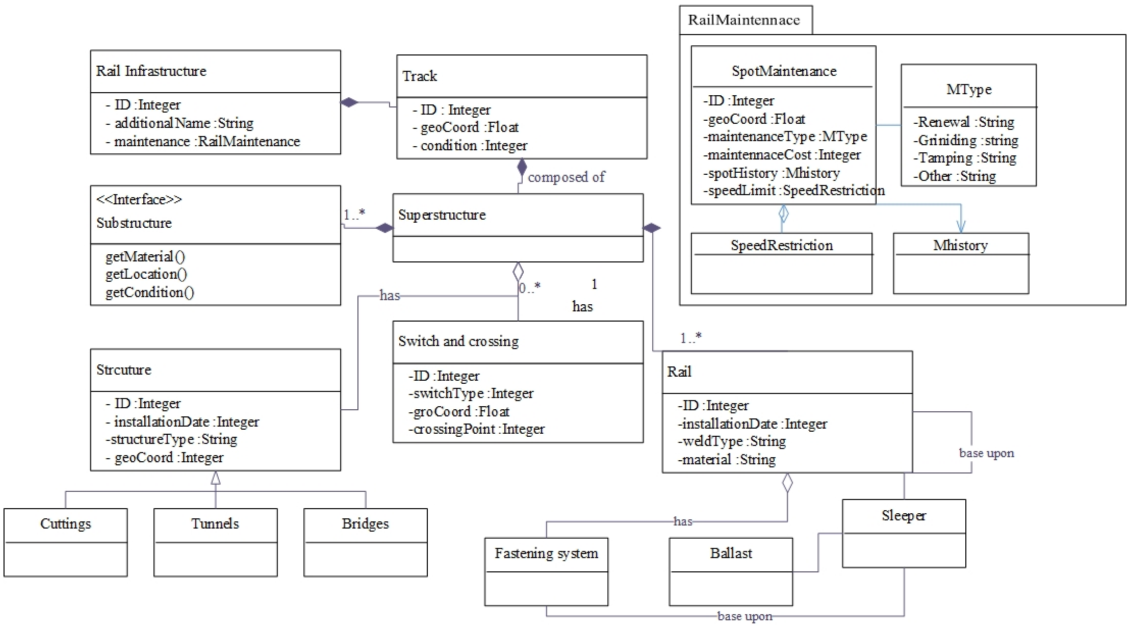

Figure 3: Information model of railway infrastructure assets

4.2.3. DSS implementation

The section outlines the details of DSS development to support the decision question. The objects mentioned in the information models (see Figure 3) are fundamental to process and support the posed decision question. For the data management, the document-based database MongoDB 3.0 is selected. The choice of this database is mainly driven by the evolving nature of data for each object, which would require the storage of related properties changing over time. The data of asset location is provided by Irish Railways. A complete network model of stations, tracks, bridges, and switches and crossing, are modeled by using Google Map API v3 (see Figure 4 for bridges).

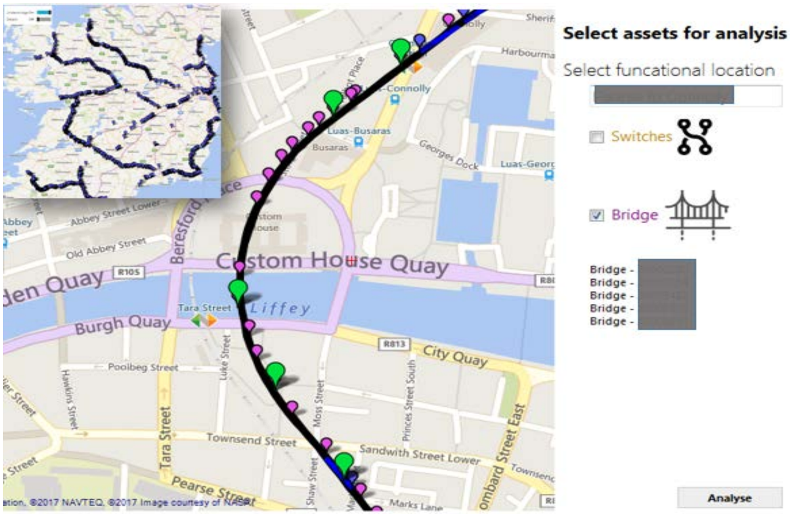

Figure 4: Visualization and selection of bridges for decision analysis

For the selection of an object for maintenance, while keeping the cost and downtime into consideration, a MCDA model based on analytical hierarchy process (AHP) is developed. For the illustration purpose, the bridges are chosen as railway objects and a limit on the number of bridges that can be selected in MCDA model at one time is set to 5 only. The detailed application of MCDA model for the bridges selection based on AHP is provided in (Allah Bukhsh et al., 2017). An infrastructure manager can choose the bridges from the network based on their functional location for the decision analysis. Figure 4 shows the procedure of bridge selection to initiate the MCDA model. Based on selected bridges, a consequence matrix is formulated where rows represent the selected bridges and columns represent decision criteria, i.e. maintenance cost, downtime, condition index and train frequency of each selected bridge (see Table 1).

Table 1: Representational data for case study

Bridges Name	Maintenance cost (euros)	Downtime (hours)	Condition Index (score card)	Train Frequency (no. trains/day)
A: Bridge 1	500k	30	2	9
B: Bridge 2	1000k	70	3	10
C: Bridge 3	200k	60	3	13
D: Bridge 4	800k	180	4	15
E: Bridge 5	500k	40	2	5

The results of MCDA model show the scoring of each bridge, when taking into account the subjective preference judgment of infrastructure managers on the objective data provided in Table 1. To illustrate, the authors played the role of decision makers, where the maintenance cost is regarded as most important, followed by downtime, condition index, and train frequency. The condition index is not regarded as most important because the performance state of bridges is assumed sufficient. Figure 5 shows detailed results of MCDA model for the five bridges. Figure 5A shows the overall ranking of bridges based on the objective of minimum cost and downtime. While, Figure 5B shows the detailed ranking. It can be noticed that the values of maintenance cost, downtime, condition index and train frequency are conflicting with each other (compare the high and low bars for a single bridge). With respect to preference structure, the higher the bar the more preferred a bridge is for maintenance for a decision criteria. If the objective is to prefer minimum cost and downtime then the preferred bridge is `C:Bridge 3', while if our consideration is to maintain a bridge with higher train frequency then `D:Bridge 4' is preferred. To minimize the interpretation complexity for infrastructure managers, the final results are illustrated on the GIS map with different color codes.

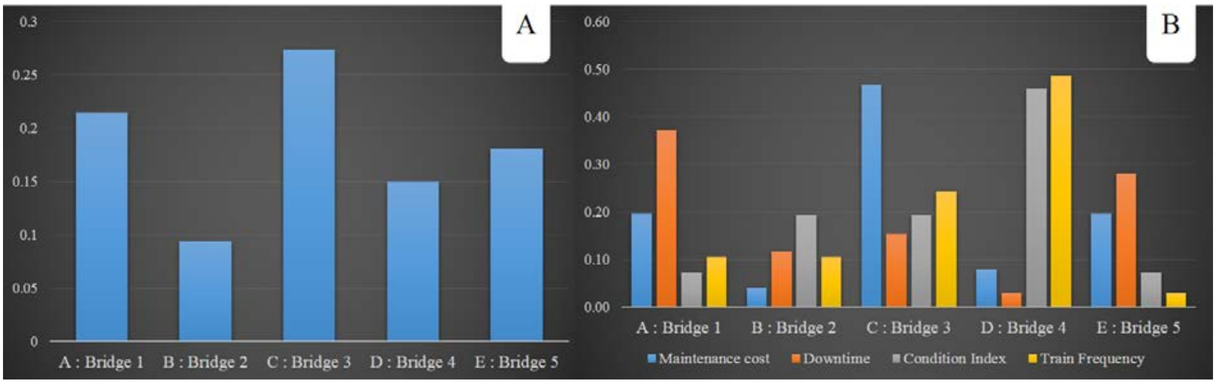

Figure 5: Results of decision analysis model for five bridges (A: Overall ranking of bridges based on minimum cost and downtime, B: Detailed ranking for each bridge with respect to their attribute)

4.2.4. DSS Evaluation

The developed DSS was evaluated by three infrastructure managers from Irish Rail. The network models are particularly found to be useful. In addition, the discussion on current practices of maintenance decision making warrants the need for a decision-driven DSS. The ability of DSS to incorporate the subjective judgments as well as the objective data makes the procedure of maintenance decision making an efficient and transparent activity.

5. Discussion

To tackle the complexity of railway maintenance decision making established on complex data management procedures, a paradigm shift from data-driven towards the decision-driven approach for the development of DSS is introduced in this paper. A case of bridge selection for maintenance planning illustrates the proposed decision-driven approach. The results of the case study show how the targeted data collection, defined in information models, leads to reduced data management overhead and facilitates the decision-making process for maintenance planning. Despite the generic nature of the posed decision question, a targeted set of data regarding the assets' location and conditions is used for railway network modeling. With the help of complete network model, an infrastructure manager is enabled to choose the railway objects at run-time for the maintenance planning and decision analysis. It can be said that the decision-driven DSS approach reduces the complexity of data collection and management procedures by putting forward a need of definite decision context. In contrast to the data-driven approach, in which data collection is an intrinsic activity, the decision-driven approach proposes to delay the data gathering activity until the definite data usage and data need has been defined by decision context.

Even though the decision-specific data collection reduced the data management overhead and directs the focus towards improving the decision analysis capabilities of DSS, some general remarks regarding the introduced decision-driven approach can be made. The decision-driven approach requires the definition of the decision context as the first step of DSS development (as demonstrated in Section 4) . The procedure of defining decision context can cause uncertainty if an experts/stakeholders are unable to identify and/or define decision scope, decision questions, and decision criteria. One of the possible solutions is to initiate by understanding the expected outcomes from the DSS. Through the process of reverse-engineering, the definite decision question along with data requirement can be defined. Moreover, in this paper, an AHP method is used to rank the railway bridges for maintenance decision, assuming that the criteria are non-conflicting and finite in nature. However, some infrastructure maintenance scenarios are posed with a number of decision-making dilemma's of conflicting objectives, in term of limited budgets, deteriorating asset conditions, and 24/7 need of availability. For the optimized maintenance solution, a trade-off among the conflicting objectives has to be defined. While, the decision-driven approach, introduced in this paper, does not provide support for the development of MCDA methods but facilitates in decision context definition only.

The proposed decision-driven approach appears to criticize the unfocused data collection activity, which is mainly derived from the need of robust decisions originated from real data. Nevertheless, data is the key to the improved decision making (Vanier, 2001) and the proposed methodology does not imply that the acquisition and management of infrastructure data should be abandoned. An independent activity to overhaul the current data silos towards the more robust integrated system will not only assist in decision making, but will also bring ease in routine operational tasks. However, the decision-driven approach suggests not to perform this large-scale system integration as a part of DSS development. Since it diverts the focus towards the data management instead of providing support in complex decision scenarios. Moreover, in a large DSS development program the data, collection procedures remain segregated from the decision analysis part where the developed decision analysis models are unable to exploit the full potential of the collected data. With the decision-driven approach, the data requirements are initiated and defined by prospective stakeholders. This decision-to-data approach will minimize the data management challenges and will strengthen decision analysis capabilities of DSS.

Finally, in the era of big data, the decision-driven approach is one step towards the smart use of data for taking the smart decisions, where a procedural flow from decision context, information model, implementations, and evaluations reduces the decisions complexity and data handling challenges. However, further research for the validation and evaluation of decision-driven approach for the development of DSS is needed.

6. Conclusion

To minimize the data management overhead, a paradigm shift from data-driven towards the decision-driven is introduced. The decision-driven approach proposed four-step procedure that aims to improve the decision-making capabilities of DSS. The proposed approach is illustrated with the help of a case study of the maintenance decision-making for bridges. By focused data collection, a complete network model of Irish rail is developed. The network model of railway yielded flexibility to infrastructure managers, where an infrastructure manager is able to choose any set of bridges for the sake of decision analysis. The complexity of maintenance decision-making is tackled by incorporating the method of MCDA in DSS implementation. Therefore, it can be concluded that the decision-driven methodology 1) define the *decision context* concretely with decision scope, decision question and criteria definition 2) minimizes the overhead of data management by focused data collection 3) makes the data-interrelationship explicit with *information modeling* 4) incorporates *the MCDA method* in the implementation phase 5) minimizes the decision-making complexity by developing intuitive interfaces and 6) enables the iterative users' feedback loop for further improvements in *DSS evaluation* phase. The future work of this study includes the further evaluation of proposed decision-driven approach applied on conflicting decision scenarios. The development of network-wide DSS based on multiple decision questions supported with required data is also part of future research efforts.

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