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PII: S0925-5273(15)00085-7
DOI: http://dx.doi.org/10.1016/j.ijpe.2015.03.017
Reference: PROECO6036

To appear in: *Int. J. Production Economics*

Received date: 14 April 2014
Accepted date: 12 March 2015

Cite this article as: Peter Chemweno, Liliane Pintelon, Adriaan Van Horenbeek, Peter Muchiri, , Development of a risk assessment selection methodology for asset maintenance decision making: An analytic network process (ANP) approach, *Int. J. Production Economics,* http://dx.doi.org/10.1016/j.ijpe.2015.03.017

Development of a risk assessment selection methodology for asset maintenance decision making: An analytic network process (ANP) approach

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Abstract

Risk assessment performs a critical decision support role in maintenance decision making. This is through assisting maintenance practitioners systematically identify, analyze, evaluate and mitigate equipment failures. Often, such failures are mitigated through formulating effective maintenance strategies. In asset maintenance, well-known risk assessment techniques include the Failure Mode and Effect Analysis (FMEA), Fault Tree Analysis (FTA), and Bayesian Networks (BN). In recent years, considerable research attention has been directed towards improving existing techniques, often at the expense of a structured framework for selecting suitable risk

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assessment techniques. Often, several criteria influence the selection process. Moreover, the criteria are closely linked to specific organizational competencies that vary from one firm to another. In this study, a selection methodology for risk assessment techniques in the maintenance decision making domain is proposed. In the methodology, generic selection criteria for the FMEA, FTA and BN are derived based on the risk assessment process outlined in the ISO 31000:2009 standard. The criteria are prioritized using the Analytic Network Process (ANP), taking into account the judgment and opinion of academic and industrial domain experts. The results illustrate the usefulness of the proposed methodology towards assisting maintenance practitioners discern important competencies relevant to the specific technique and as such select the technique best suited for the organization.

Keywords: Asset maintenance, Risk assessment, Selection methodology, ANP

1. Introduction

The importance of asset management (AM) in the context of maintenance decision making is underscored in literature (Pintelon and Van Puyvelde, 2013). This is attributed to the fact that AM focuses on managing all phases of the asset's lifecycle, right from inception to disposal. For operable assets, the operation and maintenance (O&M) phase is quite critical, often constituting as much as 70% of the asset's total cost of ownership (Koronios et al., 2007). As such, risk management forms an important aspect in AM. This is highlighted through definitions of AM reported in literature. For instance, the PAS-55 standard for asset management describes AM as "*the systematic and coordinated practices through which organizations optimally and sustainably manage its assets, asset systems, their associated performance, risks and expenditures over the asset's life-cycle for purposes of achieving the organization strategic plan*." Clearly, risk management is viewed as rather crucial with regards to mitigating equipment failures. For operable assets, this entails formulating effective maintenance strategies.

The ISO 31000:2009 standard proposes a risk management framework that embeds policies, procedures and practices throughout the organization (International Electrotechnical Commision, 2009). The standard recognizes the strategic role of risk management with regards to recognizing and as such formulating risk mitigation strategies. Within the risk management process, risk assessment (RA) provides a crucial framework for systematically identifying, analyzing, evaluating and mitigating risks. To perform risk assessment, diverse techniques exist and are applied in diverse domains, e.g. project management, insurance, banking and the manufacturing industry (Berg, 2010). How these techniques are applied for risk assessment largely depends on the nature of perceived risks and as such, their use is not generalizable across domains (Berg, 2010). Thus, depending on the specific domain, risks may be perceived as operational, technological, safety, health or political.

For the reasons mentioned above, assessing risks in one domain, e.g. in civil engineering projects differ considerably as compared to a different context, e.g. selecting appropriate maintenance strategies. Indeed, project management focuses on one-off activity and often, perceived risks may include selecting cost effective project, contractor selection, or managing project completion time (Dikmen et al., 2008). As such, techniques mentioned as deployed in project management include the Critical Path Method (CPM), Sensitivity Analysis (SA) or Monte Carlo simulation (MCS) (KarimiAzari et al., 2011). On the other hand, perceived risks in the maintenance decision making domain are largely technological given that maintenance decisions focus on the equipment's operational phase (Pintelon and Van Puyvelde, 2013). Here, the emphasis is on equipment failure modes. In this context, commonly applied techniques include the Failure Mode and Effect Analysis (FMEA), Fault Tree Analysis (FTA) and Bayesian Network (BN) (Khan and Haddara, 2003; Langseth and Portinale, 2007; Moubray, 1997).

Apart from variation in terms of perceived risks, the criteria considered while selecting risk assessment techniques also differs. For instance, in project management, Lichtenstein (1996) mentions several criteria that include the organizational structure, size and level of external party's approval. In the maintenance decision making, important criteria mentioned include the need for multi-disciplinary teams, decision support tools, reliability data and supporting technologies (Barberá et al., 2012; Khan and Haddara, 2003; Moubray, 1997). In other articles, a more general criteria is mentioned, e.g. availability of resources, degree of uncertainty or complexity of the selected technique (International Electrotechnical Commision, 2009).

From the above discussion, it is apparent that selecting suitable risk assessment techniques varies depending on among other factors, the type of technique, the application domain and nature of perceived risks. Owing to the aforementioned factors, the techniques are seldom generalizable across domains and as such, the selection process varies widely with the application context. This applies to selecting techniques in the asset maintenance domain.

The importance of selecting appropriate techniques in maintenance decision making is underscored in several studies. Braaksma et al. (2013) presents empirical evidence showing that application of the FMEA in practice does not support common postulates described in literature. One important postulate relates to the use of FMEA as a basis for formulating maintenance strategies. In this regard, the authors mention that the FMEA process is often a one-off exercise. As such, formulated strategies are seldom updated with emergence of new sources of risks. Part of the reasons mentioned for non-repetitive FMEA is the need for tacit knowledge with regards to the risk assessment process. Moreover, unavailability of documentation that aids in the process is cited as an important problem.

Bloom (2005) points out rather grimly that the success rate of implementing the Reliability Centered Maintenance (RCM) program is often low – in the range of 5-10%. It should be mentioned that the FMEA constitute core phases in the RCM program (Moubray, 1997). The authors mention several reasons for the low success rate. These include the general lack of user know-how and the need for plant schematics. Cheng et al. (2008) also highlight the link between requisite competencies and application of the FMEA in risk analysis. Examples mentioned by the authors include the need for personnel training and technological support. It is intuitive that these requisite competencies also apply to other techniques, e.g. the FTA and BN. Moreover, this highlights the need for a methodological approach for selecting appropriate techniques while at the same time, taking into account requisite competencies.

In literature, insufficient attention has been paid to formulation of a methodological framework for selecting suitable techniques. Ideally, the framework takes into account the organizational competencies with respect to applying the specific risk assessment technique. This in turn increases the chances of success when such techniques are applied for risk assessment and formulating maintenance strategies. On the other hand, the absence of such a framework could negatively influence the results of the derived maintenance strategies. This is especially the case where techniques are selected ad-hoc or based on perceived popularity, e.g. FMEA (Braaksma et al., 2013). Moreover, deriving maintenance strategies based primarily on user experience may yield inappropriate maintenance decisions. Given the strategic importance of maintenance programs towards sustaining the organizational competitiveness, the role of risk assessment cannot be ignored (Pintelon and Van Puyvelde, 2013). For this reason, a structured methodology for selecting appropriate risk assessment techniques is proposed. The methodology takes into account the organizational competencies. Moreover, the competencies are prioritized using the Analytic Network Process (ANP) methodology. The derived competencies are generic and as such applicable across different techniques.

This paper is organized as follows. Section 2 describes the implicit link between risk assessment and asset maintenance. This is followed by a brief review of classification schemes for risk assessment techniques and existing selection frameworks applied in different domains. Section 3 outlines the methodological steps adopted in this article, starting with deriving the generic selection criteria and followed by prioritizing the competencies using the ANP methodology. Section 4 describes the approach applied for deriving the generic competencies. Section 5 discusses the ANP methodology as applied for prioritizing competencies for the FMEA, FTA and BN. Section 6 illustrates industrial application and recommended use for the selection framework. Section 7 presents general guidelines for use, while Section 8 presents discussion and managerial implications of the proposed methodology. Section 9 draws important conclusions and directions for future work.

2. Theoretical Background

2.1 Situating risk assessment in maintenance decision making

In operable assets, equipment failure is regarded as an important risk aspect. This is due to the fact that asset failure is often associated with consequences that may be economic, environment and/or safety in nature (Khan and Haddara, 2003). For instance, a sheared component may injure the operator, cause spillage and moreover, lead to high repair costs. For this reason, formulating mitigation strategies through asset maintenance programs is rather important (Pintelon and Van Puyvelde, 2013). Often, such programs ideally encompass two core aspects; *maintenance policy* selection, and determining appropriate *maintenance actions*. Maintenance actions imply the elementary interventions performed by the technician in response to the equipment state or condition and may include preventive or restorative actions. Maintenance actions are largely linked to the type of maintenance policy. For instance, corrective maintenance actions are often undertaken in the Failure Based Maintenance (FBM) policy. On the other hand, preventive repair actions are carried out in the Time/Use Based Maintenance (TBM/UBM) policy (Pintelon and Van Puyvelde, 2013). Other well-known maintenance policies include the Condition Based Maintenance (CBM) and Opportunity Based Maintenance (OBM).

When selecting the right maintenance strategy, risk assessment performs a crucial role. Here, the risk assessment provides an important decision support structure that aids the selection process. Decision support frameworks mentioned in literature where risk assessment is embedded include the Reliability Centered Maintenance (Moubray, 1997) and Risk Based Inspection and Maintenance (RBIM) (Khan and Haddara, 2003). Notably, the FMEA is an essential technique in the RCM methodology. On the other hand, the FTA is embedded in RBIM. These techniques aid in criticality assessment where maintenance strategies are assigned on the basis of the criticality of the equipment failure mode. Though viewed as a stand-alone technique, the Bayesian Network is an important technique in the sense that it attempts to replicate the FTA's formalism, more so, with respect modelling system dependencies. The dependencies may be technical (i.e. inter-linkage between components), functional or logical (e.g. failure sequence) (Van Horenbeek et al., 2010).

In their initial form, the FMEA, FTA and BN are somewhat classical and standard risk assessment techniques. For instance, the FMEA defines the Risk Priority Number (RPN) as a measure of failure mode criticality. On the other hand, the FTA defines a formal hierarchical structure based on binary gates. The BN incorporates conditional probabilities as a measure of combinatorial dependencies between failure events. Nonetheless, recent years has seen a proliferation of alternative techniques for the FMEA, FTA and BN. These techniques aim at improving well-known deficiencies associated with the classical approaches, e.g. the RPN form or non-inclusion of temporal aspects associated with operable assets (Čepin and Mavko, 2002; Liu et al., 2013; Weber et al., 2012). For FMEA, Liu et al. (2013) notes the availability of numerous alternative techniques. For FTA, Chiacchio et al. (2011) distinguishes between static and dynamic techniques depending on how temporal aspects are taken into account. For the BN, Weber et al. (2012) also distinguished between static and dynamic techniques.

Moreover, the alternative techniques for FMEA, FTA and BN range from fairly simple to rather complex approaches. For instance, several techniques incorporate solution algorithms based on, e.g. fuzzy logic or linear programming, further increasing the computational complexities. As such, applying the improved techniques is not straightforward. For instance here, user know-how becomes quite important, further complicating the selection process for the appropriate technique. This leads to important questions regarding the selection problem:

(i) Which techniques are best suited for the organization taking into account the organizational competencies?
(ii) Which competencies should the organization focus on prior to applying the selected risk assessment technique?

A framework addressing these questions is seldom discussed in literature. This research study addresses this gap by proposing a conceptual methodology for selecting suitable risk assessment techniques. The main motivation of the research is to provide practitioners with a structured approach for selecting appropriate techniques while taking into account the requisite organizational competencies. Invariably, this enhances the maintenance decision support with regards to selecting appropriate maintenance strategies.

2.2 Risk assessment classification and selection schemes

Despite the important role risk assessment techniques perform in maintenance decision making, methodological approaches that assist practitioners select suitable techniques is missing in literature. Instead, existing work largely focus on reviewing existing techniques and on the basis of the review, propose classification schemes, e.g. see (Arunraj and Maiti, 2010; Faber and Stewart, 2003; Marhavilas et al., 2011; Tixier et al., 2002). The schemes often vary according to the specific author and may take into account aspects such as the type of input data, type of technique, or output data generated from the specific technique. However, these schemes often lack a formal structure that could aid practitioners select a suitable technique. Moreover, the techniques mentioned in these schemes are seldom linked to specific competencies necessary for performing risk assessment.

The ISO/IEC 31010 standard for risk assessment techniques propose several attributes necessary for applying generic risk assessment techniques (International Electrotechnical Commision, 2009). However, the proposed attributes are rather general and seldom linked to specific competencies. For instance, the standard mentions attributes, e.g. resource capacity or complexity of the specific technique. It should be mentioned that such attributes are vague and not linked to specific competencies, e.g. personnel skills or documentation. Moreover, the standard applies a qualitative ranking (i.e. low, medium and high) for evaluating the suitability of the specific technique. However, such ranking can be quite restrictive and moreover lacks the comprehensiveness required for selecting techniques in the real world setting.

Dey and Ogunlana (2004) propose a model for selecting techniques applicable in build-operate-transfer projects. The model is based on logical decision trees with the selected technique derived through a binary query process. However, the techniques evaluated in the study apply to the project management domain, thus not generalizable to maintenance decision making. Moreover, no reference is made to appropriate competencies necessary for applying the mentioned techniques in risk assessment. Moreover, the logical decision making approach proposed in the article exposes the selection exercise to considerable bias especially where several decision makers are involved.

Recently, KarimiAzari et al. (2011) propose a model for selecting techniques applicable in the construction industry. The model formulates the selection problem as Multi Criteria Decision Making (MCDM) problem and based on the Fuzzy Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) methodology (Tzeng and Huang, 2011). Similar to the aforementioned article, the techniques evaluated in the selection model apply to the project management domain, thus not generalizable to maintenance decision making. Moreover, the authors fail to link the mentioned techniques to the competencies necessary for application in risk assessment.

The deficiencies discussed in the previous paragraphs are addressed by the selection methodology proposed in this article. Firstly, requisite competencies necessary for applying specific techniques are derived from literature. Moreover, the derived competencies are generic and as such, applicable to the FMEA, FTA and BN techniques. The competencies are also linked to the risk assessment steps outlined in the ISO 31000:2009 standard. The competencies are prioritized using the ANP methodology. This way, decision makers are able to select techniques best suited for the organization, given the often varying organizational competencies. Moreover, the selection methodology avoids the need for selecting techniques in an ad-hoc manner, which as earlier mentioned may yield inappropriate maintenance decisions.

3. Risk assessment selection methodology

The selection methodology discussed in this article consists of four main phases depicted in Figure 1. The steps are as follows:

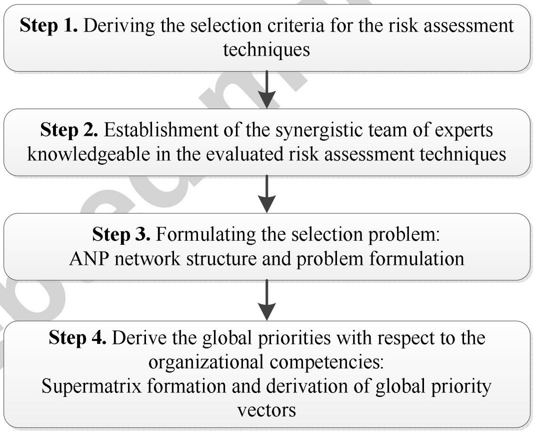

Figure 1: Methodological steps

Step 1. Deriving the generic selection criteria: In this step, the selection criteria are derived, first by linking different competencies to the specific techniques and secondly, linking the competencies to the ISO 31000:2009 risk assessment steps. The techniques considered in the derivation process are the FMEA, FTA and BN. For FMEA, both the classical and quantitative techniques are considered. For the FTA and BN, the static and dynamic techniques are included.

Step 2. Establishment of the team of experts: The experts participating in the group decision process are selected by virtue of their knowledge with respect to applying specific risk assessment techniques in asset maintenance.

Step 3. Formulating the decision problem and constructing the ANP network structure: In this step, a careful formulation of the decision problem is undertaken. Here, the decision making process is adapted whereby group decisions are reached through a consensus vote. On the basis of the decision problem, the ANP network structure is formulated.

Step 4. Derive the global priorities: In this step, the selection criteria are prioritized with respect to the specific techniques. Here, the ANP methodology is adopted. Prioritizing the competencies assists decision makers select the suitable technique while taking into account the intrinsic organizational competencies.

4. Deriving the generic selection criteria

Deriving the selection criteria takes into account the practicality and exhaustiveness necessary for applying the techniques in risk assessment. The criteria are derived through a systematic literature search where specific competencies necessary for applying the different techniques are discussed. An overview of the derived criteria and citations are presented in Table 1.

In the derivation process, the risk assessment process described in the ISO 31000:2009 is adapted (see Figure 2). Three important steps are mentioned in the standard, namely: (1) risk identification; (2) risk analysis; and (3) risk evaluation. The forth step, i.e. risk mitigation, entails implementing effective maintenance strategies, achieved through selecting appropriate maintenance policy. The forth step is beyond the scope of this article, thus not discussed.

Ideally, each risk assessment technique follows the steps depicted in Figure 2. Closely linked to these steps are several requisite competencies that influence how each technique is applied for assessing risks in operable assets. As mentioned earlier, the selection criteria is rather important given that a firm lacking certain competencies, e.g. personnel expertise or reliability database may be disadvantaged with regards to applying a specific technique.

As an illustration, consider the case where the FMEA technique is used. At the *risk identification* step, failure modes are identified. To aid in the identification process, ‘decision support tools’ e.g. Piping and Instrumentation Diagrams (P&ID) and ‘maintenance records’ may prove useful. The support tools facilitate ‘functional analysis’ by identifying functional failures (MIL-STD-1629A, 1980; Moubray, 1997). Moreover, defining such failures requires an understanding of the equipment performance. As such, ‘performance assessment’ becomes necessary where ‘system loss indicators’ are defined and catalogued. In addition, the maintenance staff should possess skills necessary to interpret the ‘process description diagrams’ (e.g. the P&ID) and also perform the functional analysis. Thus, important decision criteria for the FMEA at the risk identification step include decision support tools, performance assessment, in-depth understanding of the RCM methodology and personnel skills.

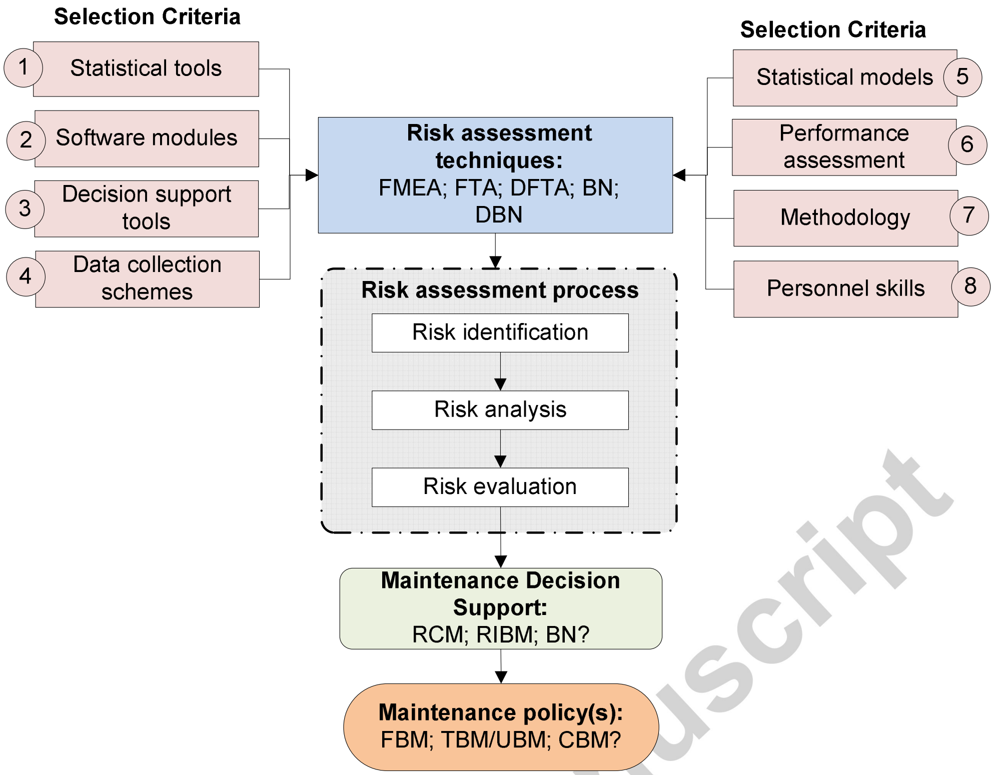

Figure 2: A summary of linkage between the selection criteria and risk assessment

At the *risk analysis step,* possible causes and potential consequences for functional failures are analyzed. Here, several decision elements are required. For instance, 'operation and maintenance records' may catalogue potential causes identified during the equipment repair process. On the other hand, records on spare parts requisition, manpower hours, spare part order lead time and production loss may assist in computing potential consequences, in this case, cost of failure. Of course, supporting technologies e.g. 'computerized maintenance management system' with extended software modules, e.g. 'maintenance budget control' may provide decision support (Barberá et al., 2012; Echeverry and Leverette, 2004). Moreover, 'reliability databases' may be linked to 'customized FMEA software' where reliability analysis is derived using appropriate 'statistical models' (Barberá et al., 2012; Relex, 2010). As such, important risk metrics such as probability of failure may be computed from 'failure functions', e.g. Weibull or logistic distribution functions (Braaksma et al., 2012). Of course, using the FMEA software requires appropriate 'personnel skills'. It should be mentioned that competencies such as reliability databases, software tools and personnel competencies also apply to alternative FMEA techniques, e.g. quantitative FMEA (Braaksma et al., 2013). The *risk evaluation step* establishes the acceptable risk threshold for asset failures. As such, competencies such as 'maintenance cost records', or 'maintenance cost database' are quite important (Echeverry and Leverette, 2004).

The deductive reasoning approach discussed in the previous paragraphs is likewise adopted for the FTA and BN. It is important to mention that the criteria deduced for the FMEA likewise applies to the FTA and BN. This is due to the fact that FMEA, FTA and BN techniques follow the risk assessment process depicted in Figure 2. However, the criteria may vary in importance depending on the specific technique. For instance, the reliability database may be perceived as more important with regard to the FTA as compared to the classical FMEA approach. For the BN, availability of software tools and personnel expertise on statistical theory may be perceived as overriding competencies. As such, the derived criteria depicted in Table 1 may be seen as generic, thus applying across the techniques. The variation in importance is seen as important motivation for formulating the selection process as a MCDM problem.

In total, 30 selection criteria are identified and grouped into 8 decision clusters as depicted in Table 1. Formulating the selection problem and applying the ANP methodology is discussed next in Section 5.

	Decision Criteria	Decision elements	Author
SC 1	Software tools	(1) Computerized maintenance management software; (2) Enterprise asset management; (3) Enterprise resource planning; (4) Customized risk assessment software, e.g. RelexFMEA®, Hugin®, ISOGRAPH®.	Barberá et al. (2012); Echeverry and Leverette (2004); Čepin and Mavko (2002); Khakzad et al. (2013); Langseth and Portinale (2007); Jones et al. (2010); Relex (2010); Braaksma et al. (2012).
SC 2	Software modules	(1) Maintenance budget control; (2) Decision support module; (3) Report generation module; (4) Configuration management module.	Barberá et al. (2012); Echeverry and Leverette (2004); Braaksma et al. (2013); (Khan and Haddara, 2003); Celeux et al. (2006).
SC 3	Decision support tools	(1) Process description diagrams, e.g. piping and instrumentation diagram (P&ID); (2) Operating and maintenance records; (3) Analytic logical techniques: e.g. fault tree, event trees, directed acyclic graph; (4) Conditional probability tables.	Barberá et al. (2012); Echeverry and Leverette (2004); Moubray (1997); MIL-STD-1629A (1980); Khan and Haddara (2003); Volkanovski et al. (2009); Čepin and Mavko (2002); Jones et al. (2010); Langseth and Portinale (2007); Weber et al. (2012).
SC 4	Data collection schemes	(1) Reliability databases; (2) Maintainability database; (3) Operation and maintenance cost database; (4) Safety and environmental database.	Barberá et al. (2012); Echeverry and Leverette (2004); Moubray (1997); Khan and Haddara (2003); Braaksma et al. (2012); Volkanovski et al. (2009); Čepin and Mavko (2002); Jones et al. (2010); Celeux et al. (2006); Weber et al. (2012). Langseth and Portinale (2007).
SC 5	Statistical models	(1) Maintenance optimization models; (2) Deterioration models, e.g. corrosion/wear models; (3) Maintainability assessment models, e.g. imperfect maintenance models; (4) Failure functions, e.g. Weibull distribution; (5) Inference algorithms, e.g. Markov chain Monte Carlo.	Echeverry and Leverette (2004); Braaksma et al. (2012); Crocker and Kumar (2000); Khan and Haddara (2003); Čepin and Mavko (2002); Langseth and Portinale (2007); Jones et al. (2010); Weber et al. (2012); Cai et al. (2013).
SC 6	Performance measurement	(1) Functional analysis statements; (2) Maintenance performance indicators; (3) System loss indicators.	Echeverry and Leverette (2004); MIL-STD-1629A (1980); (Khan and Haddara, 2003); Moubray (1997); Khakzad et al. (2013); Langseth and Portinale (2007).
SC 7	Methodology /procedure	(1) Reliability centered maintenance; (2) Risk based inspection and maintenance; (3) Bayesian inference statistics.	Echeverry and Leverette (2004); Moubray (1997); Khan and Haddara (2003); MIL-STD-1629A (1980); Volkanovski et al. (2009); Langseth and Portinale (2007).
SC 8	Personnel skills	(1) Facilitators (statistician); (2) Multi-disciplinary teams; (3) Expert elicitation techniques; (4) Knowledge and skills matrix	Echeverry and Leverette (2004); MIL-STD-1629A (1980); Moubray (1997); Braaksma et al. (2013); Braaksma et al. (2012); Celeux et al. (2006); Langseth and Portinale (2007); Weber et al. (2012).

Table 1: Summary of selection criteria and respective decision elements for FMEA, FTA and BN

5. Analytic network process (ANP) methodology

In this section, the remaining 3 steps of the methodology are discussed. These include establishing the team of experts, formulating the selection problem, structuring the ANP network and deriving the priority weights.

The ANP is a generalization of the analytic hierarchy process (AHP) and considered an ideal tool for resolving complex decision making problems (Saaty, 2004). Unlike the AHP where the decision problem is structured in a hierarchical form, in ANP, the decision problem is structured in a network form. Here, the decision clusters and elements are connected through network links. The links express the dependencies amongst the clusters and elements. Dependencies between elements in the same decision cluster are represented through *inner dependencies* while dependencies between elements in one cluster and those in a different cluster are represented through *outer dependencies* (Saaty, 2004).

The ANP methodology is considered an ideal choice for formulating the selection problem for several reasons. Firstly, the ANP is suitable for solving complex decision problems that are multi-criteria in nature. Often, real-life decision problems are rather complex and as such there is the need to take into account trade-offs between both tangible and intangible decision criteria (Saaty, 2004). To account for these trade-offs, the ANP methodology allows decision makers to express their preference between decision elements through the reciprocal pairwise comparison process. This comparison is based on the Saaty's fundamental scale (Saaty, 1990). Moreover, consistency in the decision making process is evaluated through computing the Consistency Ratio (CR).

Moreover, the ANP methodology takes into account interdependencies between clusters and decision elements in the ANP network structure. For instance, the criterion 'software tools' is dependent on 'personnel skills'. Taking into account these dependencies is important with regards to deriving the overall priorities. Indeed, aspects ranked as less important using hierarchical MCDM approaches, e.g. AHP may in fact rank as more important when network dependencies are taken into account (Saaty, 2004).

The ANP methodology applies the eigenvalue method as the primary technique for deriving overall priorities. However, there is considerable criticism regarding the eigenvalue approach, e.g. see Bana e Costa and Vansnick (2008). Much of the criticism relates to the rank reversal phenomena often attributed to the eigenvalue method. Nonetheless, such criticisms are countered by several authors, e.g. Wang et al. (2009) where the robustness of the eigenvalue method with respect to preserving priority ranking is validated through numerical illustrations. Moreover, Ishizaka and Labib (2011) assert that the link between the eigenvalue method and the rank reversal phenomena remains largely unresolved. For this reason, the robustness of the eigenvalue approach as applied in the ANP methodology is not negated. Indeed, applicability of the eigenvalue methodology in ANP is demonstrated in several studies, e.g. maintenance performance measurement (Van Horenbeek and Pintelon, 2014), maintenance strategy evaluation (Jajimoggala et al., 2011), and outsourcing decision making (Tjader et al., 2014).

5.1 Application of ANP methodology for the selection problem

5.1.1 Establish the team of experts

Given that decisions in the pairwise comparison process involve several persons, group decision making is often suggested. This way, bias associated with judgment expressed by a single expert is avoided (Ishizaka and Labib, 2011). When formulating group decisions, the role of a synergistic team of experts is underscored. Here, the synergistic team differs from a collection of individuals, but rather implies a team that is knowledgeable with the decision problem at hand (Ishizaka and Labib, 2011).

Moreover, formulating representative group decisions is viewed as an important challenge with respect to multiple decision makers. For this reason, several authors, e.g. Dyer and Forman (1992) propose several approaches that include the consensus vote method and aggregation (e.g. the geometric mean). While Aczél and Saaty (1983) mention the geometric mean as the correct approach for synthesizing group decisions, other authors, e.g. Van Horenbeek and Pintelon (2014) caution that aggregating group decisions prior to understanding the decision problem (i.e. discussed in a group session) only yields averaged individual decisions that are not necessarily representative. Moreover, the consensus vote is mentioned as an important cognitive decision making approach where the synergistic team is involved (Janis, 1989). For this reason, the consensus vote is adapted in this study. In consensus voting, the team of experts deliberate and reach an agreement on the pairwise comparison value that is afterwards entered in the ANP matrix.

However, several authors criticize the aspect of assigning crisp pairwise comparison values, e.g. see (Büyüközkan et al., 2011; Chamodrakas et al., 2010; Lupo, 2013). Instead, the authors suggest a fuzzy scale that takes into account the uncertainty and imprecise nature of the elicited crisp values. While it is argued that the fuzzy methodology improves the pairwise comparison process, the premise/validity of the crisp scale is not negated. Indeed, authors, e.g. Saaty (2004), argues that the imprecision of the crisp values is satisfactorily addressed by the eigenvalue method. Moreover, Wang et al. (2009) shows using numerical illustrations that the consistency ratio (CR) is a rather good measure of the impreciseness of elicited decisions. For these reasons, the eigenvalue approach is considered robust enough.

Nonetheless, a careful selection of decision makers is performed and takes into account aspects such as the experts understanding of the specific risk assessment techniques. The experts are drawn from academia and industry and knowledgeable on two techniques, i.e. the FMEA and FTA. The BN on the other hand is found to be scarcely applied in industry thus not evaluated by the industrial experts. Nonetheless, the BN is discussed here for illustrative purposes where the pairwise comparison process is based on the authors' experience. The objective of including the BN in the comparison process is to illustrate the versatility of the derived generic criteria as the basis for comparing multiple risk assessment techniques.

The team of industrial experts evaluating the FMEA and FTA combine experience gained while working for a well-known European automobile manufacturer. The academicians' core area of interest is asset maintenance. Following the approach proposed in Van Horenbeek and Pintelon (2014), a generic ANP network structure depicted in Figure 3 is formulated to aid in the decision making process.

5.1.2 Model development and problem formulation

Figure 3 depicts the ANP network structure consisting of 30 decision elements grouped into 8 decision clusters depicted in Table 1. The decision clusters are represented by nodes, while the dependencies amongst the clusters are represented by arcs. Depending on the nature of the dependencies, the arcs are of two types; *two-way* arrows and *looped arc*. The two-way arrow depicts outer dependence, e.g. between the clusters 'software tools' and 'personnel skills'. On the other hand, the *looped arc* depict inner dependence amongst elements in a decision cluster, e.g. between elements in the cluster 'decision support tools'.

The outer and inner dependencies are defined with respect to a control criterion, in this case, selecting the specific risk assessment technique, e.g. FMEA. For this reason, the ANP network varies depending on the specific technique. Moreover, the network depicted in Figure 3 may be considered generic, thus applying to the FMEA, FTA and BN. Here, depending on the type of technique, the network may be customized by adding or omitting decision cluster/elements or modifying the network links. For instance, the cluster "data collection schemes" may be omitted when evaluating the classical FMEA selection problem. This is intuitive considering the classical FMEA largely relies on estimates derived from multi-disciplinary teams instead of historical data.

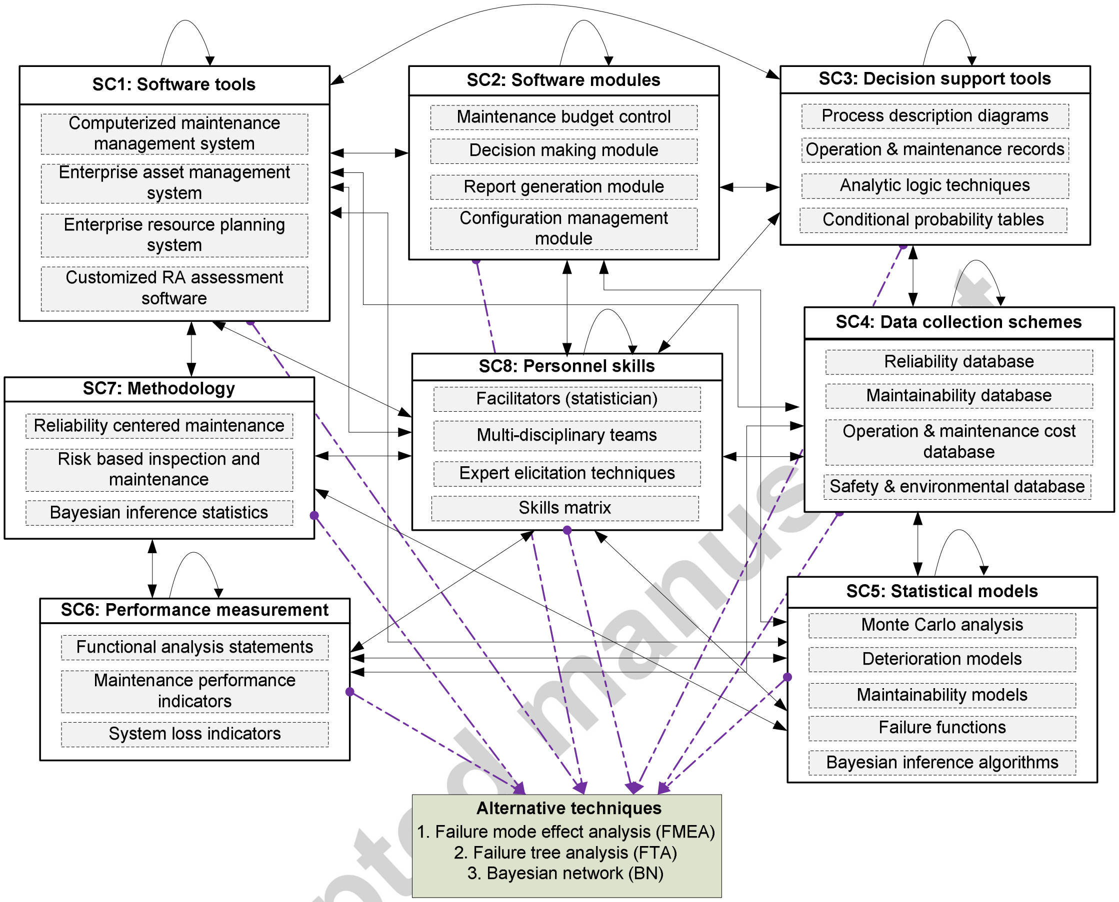

Figure 3: The conceptual ANP model

5.1.3 Pairwise comparison and consistency check

In the reciprocal pairwise comparison process, the relative importance of the clusters/elements is established based on the Saaty's scale. For detailed information on the pairwise comparison process, the interested reader is referred to the work of Saaty (Saaty, 2004). Table 2 depicts the pairwise comparison for the decision cluster 'software tools' with respect to the selecting the FMEA technique. Table 3 on the other hand depicts the pairwise comparison matrix for the decision clusters. Table 2 and Table 3 represent the inner and outer dependencies respectively with respect to selecting the FMEA technique.

To facilitate the pairwise comparison process, the expert opinion are elicited based on the following questions (Saaty, 1996):

1. With respect to selecting a specific risk assessment technique, which of two criterions is dominant?
2. Which of the two criterions influences a third element and how strongly with respect to selecting the risk assessment technique?

The elicited responses are afterwards translated into numerical scores. It should be mentioned that the FTA and BN are evaluated as a family of techniques rather than their respective alternatives, e.g. dynamic FTA/BN. However, these alternatives may be included in the analysis in a rather straightforward way. This is through customizing the ANP network with respect to the specific technique, i.e. by omitting/including decision elements and/or clusters as earlier mentioned. Moreover, the ANP network links may also be modified to represent the perceived dependencies with respect to the alternative technique, thus the ANP network structure may also be seen as generic.

For brevity, the following paragraphs illustrate the case of prioritizing criteria with respect to selecting the FMEA technique. First, the ANP network depicted in Figure 3 is customized by omitting the decision cluster ‘methodology’ and the decision elements ‘configuration management’, ‘report generation module’, ‘analytic logic techniques’, ‘conditional probability table’, ‘deterioration models’ and ‘maintainability models’. The cluster ‘methodology’ is omitted owing to the fact that the FMEA technique is linked to the RCM methodology. The decision elements are omitted due to their perceived limited influence with respect to applying the FMEA technique. For instance, the ‘analytic logic techniques’ and ‘conditional probability tables’ are linked to the FTA and BN techniques respectively, thus not essential with respect to the FMEA. However, it is worth noting that the element ‘reliability database’ is retained. This is attributed to its importance with respect to the quantitative FMEA technique where the risk metric, probability of failure, is derived from reliability analysis. As such, historical failure database is important.

For the FMEA selection problem, pairwise comparison matrices were derived from the customized ANP network. For each matrix, the priority vectors are derived through computing the principal eigenvector which upon normalization transforms to local priority values (Saaty, 2004). The same approach is adapted for the FTA and BN.

Table 2: Pairwise comparison for elements in the decision support tools cluster

Pairwise comparison of decision elements within the software tools cluster with respect to FMEA			
FMEA	CMMS	EAM	FMEA software
Computerized maintenance management system (CMMS)	1	1	1/4
Enterprise asset management (EAM)	1	1	1/4
Customised FMEA software	4	4	1
Local priorities	0.167	0.167	0.667
Consistency Ratio (CR)		0	

As depicted on Table 2 and Table 3, the most important decision element on the basis of local priorities is the ‘FMEA software’. On the other hand, the CMMS and EAM are perceived to be of equal importance. From Table 3, the most important decision clusters include ‘personnel skills’ followed by ‘decision support tools’. The derived local priority values form the basis of forming the ANP supermatrices, further discussed in Section 5.1.4.

For each matrix, a consistency check is performed to evaluate consistency in the decision making process. A consistency ratio (CR) of 0.1 or less is indicative of consistency. Thus, the pairwise comparison values for Tables 2 and 3 fulfil the consistency requirements.

Table 3: Pairwise comparison for the decision clusters with respect to FMEA

Pairwise comparison of the decision clusters with respect to selecting the FMEA							
FMEA	SC 1	SC 2	SC 3	SC 4	SC 5	SC 6	SC 8
Software tools	1	3	1/4	3	3	1/4	1/5
Software modules	1/3	1	1/5	1/4	1/4	1/3	1/6
Analysis/decision support tools	4	5	1	4	3	2	1/5
Data collection schemes	1/3	4	1/4	1	1	1/3	1/5
Statistical models	1/3	4	1/3	1	1	1/4	1/5
Performance measurement	4	3	1/2	3	4	1	1/5
Personnel skills	5	6	5	5	5	5	1
Local priorities	0.1003	0.0352	0.1974	0.0750	0.0745	0.1495	0.3681
Consistency ratio (CR)				0.096			

5.1.4 Supermatrix formation and deriving global priority weights

The unweighted supermatrix is constructed using the local priority values derived from the pairwise comparison matrices. The unweighted supermatrix is normalized by making the sum of each column equal to one, thus transforming to the weighted supermatrix. Next, the weighted supermatrix is raised to arbitrary large numbers, i.e. the power $2k+1$ up until convergence is reached. At convergence, further raising the supermatrix to powers does not significantly change the matrix values (Saaty, 2004). The convergence supermatrix (i.e. limit supermatrix) for the FMEA selection problem is depicted in Table 4 and represents the global priority vectors for the FMEA selection problem. Although evaluated using the aforementioned approach, the limit supermatrix for the FTA and BN are not depicted for the purpose of brevity.

Table 4: Limit supermatrix for FMEA selection.

	FMEA	SC 1	SC 2	SC 3	SC 4	SC 5	SC 6	SC 8	CMMS	EAM	FMEA®	PDD	O&M-R	RD	O&MC-D	FF	MC	FAS	MPI	SLI	F	MDT	ELT	K&SM
FMEA	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Software tools (SC 1)	0.033	0.033	0.033	0.033	0.033	0.033	0.033	0.033	0.033	0.033	0.033	0.033	0.033	0.033	0.033	0.033	0.033	0.033	0.033	0.033	0.033	0.033	0.033	0.033
Software modules (SC 2)	0.022	0.022	0.022	0.022	0.022	0.022	0.022	0.022	0.022	0.022	0.022	0.022	0.022	0.022	0.022	0.022	0.022	0.022	0.022	0.022	0.022	0.022	0.022	0.022
Decision support tools (SC 3)	0.039	0.039	0.039	0.039	0.039	0.039	0.039	0.039	0.039	0.039	0.039	0.039	0.039	0.039	0.039	0.039	0.039	0.039	0.039	0.039	0.039	0.039	0.039	0.039
Data collection schemes (SC 4)	0.035	0.035	0.035	0.035	0.035	0.035	0.035	0.035	0.035	0.035	0.035	0.035	0.035	0.035	0.035	0.035	0.035	0.035	0.035	0.035	0.035	0.035	0.035	0.035
Statistical models (SC 5)	0.037	0.037	0.037	0.037	0.037	0.037	0.037	0.037	0.037	0.037	0.037	0.037	0.037	0.037	0.037	0.037	0.037	0.037	0.037	0.037	0.037	0.037	0.037	0.037
Performance measurement (SC 6)	0.025	0.025	0.025	0.025	0.025	0.025	0.025	0.025	0.025	0.025	0.025	0.025	0.025	0.025	0.025	0.025	0.025	0.025	0.025	0.025	0.025	0.025	0.025	0.025
Personnel skills (SC 8)	0.087	0.087	0.087	0.087	0.087	0.087	0.087	0.087	0.087	0.087	0.087	0.087	0.087	0.087	0.087	0.087	0.087	0.087	0.087	0.087	0.087	0.087	0.087	0.087
Computerised maintenance management system (CMMS)	0.056	0.056	0.056	0.056	0.056	0.056	0.056	0.056	0.056	0.056	0.056	0.056	0.056	0.056	0.056	0.056	0.056	0.056	0.056	0.056	0.056	0.056	0.056	0.056
Enterprise asset management (EAM)	0.037	0.037	0.037	0.037	0.037	0.037	0.037	0.037	0.037	0.037	0.037	0.037	0.037	0.037	0.037	0.037	0.037	0.037	0.037	0.037	0.037	0.037	0.037	0.037
Customised FMEA software (FMEA®)	0.054	0.054	0.054	0.054	0.054	0.054	0.054	0.054	0.054	0.054	0.054	0.054	0.054	0.054	0.054	0.054	0.054	0.054	0.054	0.054	0.054	0.054	0.054	0.054
Process description diagrams (PDD)	0.070	0.070	0.070	0.070	0.070	0.070	0.070	0.070	0.070	0.070	0.070	0.070	0.070	0.070	0.070	0.070	0.070	0.070	0.070	0.070	0.070	0.070	0.070	0.070
Operation and maintenance records (O&M-R)	0.031	0.031	0.031	0.031	0.031	0.031	0.031	0.031	0.031	0.031	0.031	0.031	0.031	0.031	0.031	0.031	0.031	0.031	0.031	0.031	0.031	0.031	0.031	0.031
Reliability database (RD)	0.091	0.091	0.091	0.091	0.091	0.091	0.091	0.091	0.091	0.091	0.091	0.091	0.091	0.091	0.091	0.091	0.091	0.091	0.091	0.091	0.091	0.091	0.091	0.091
Operation and maintenance cost database (O&MC-D)	0.030	0.030	0.030	0.030	0.030	0.030	0.030	0.030	0.030	0.030	0.030	0.030	0.030	0.030	0.030	0.030	0.030	0.030	0.030	0.030	0.030	0.030	0.030	0.030
Failure functions (FF)	0.074	0.074	0.074	0.074	0.074	0.074	0.074	0.074	0.074	0.074	0.074	0.074	0.074	0.074	0.074	0.074	0.074	0.074	0.074	0.074	0.074	0.074	0.074	0.074
Monte carlo analysis (MC)	0.049	0.049	0.049	0.049	0.049	0.049	0.049	0.049	0.049	0.049	0.049	0.049	0.049	0.049	0.049	0.049	0.049	0.049	0.049	0.049	0.049	0.049	0.049	0.049
Functional analysis statements (FAS)	0.053	0.053	0.053	0.053	0.053	0.053	0.053	0.053	0.053	0.053	0.053	0.053	0.053	0.053	0.053	0.053	0.053	0.053	0.053	0.053	0.053	0.053	0.053	0.053
Maintenance performance indicators (MPI)	0.014	0.014	0.014	0.014	0.014	0.014	0.014	0.014	0.014	0.014	0.014	0.014	0.014	0.014	0.014	0.014	0.014	0.014	0.014	0.014	0.014	0.014	0.014	0.014
System loss indicators (SLI)	0.020	0.020	0.020	0.020	0.020	0.020	0.020	0.020	0.020	0.020	0.020	0.020	0.020	0.020	0.020	0.020	0.020	0.020	0.020	0.020	0.020	0.020	0.020	0.020
Facilitator/statistician (s) (F)	0.040	0.040	0.040	0.040	0.040	0.040	0.040	0.040	0.040	0.040	0.040	0.040	0.040	0.040	0.040	0.040	0.040	0.040	0.040	0.040	0.040	0.040	0.040	0.040
Multi-disciplinary teams (MDT)	0.027	0.027	0.027	0.027	0.027	0.027	0.027	0.027	0.027	0.027	0.027	0.027	0.027	0.027	0.027	0.027	0.027	0.027	0.027	0.027	0.027	0.027	0.027	0.027
Expert elicitation techniques (ELT)	0.017	0.017	0.017	0.017	0.017	0.017	0.017	0.017	0.017	0.017	0.017	0.017	0.017	0.017	0.017	0.017	0.017	0.017	0.017	0.017	0.017	0.017	0.017	0.017
Knowledge/skills matrix (K&SM)	0.058	0.058	0.058	0.058	0.058	0.058	0.058	0.058	0.058	0.058	0.058	0.058	0.058	0.058	0.058	0.058	0.058	0.058	0.058	0.058	0.058	0.058	0.058	0.058

5.2 *Analysis of illustrative case results: prioritized selection decision elements*

Figure 4 illustrates the limit priority vectors for selecting the FMEA, FTA and BN. The FMEA and FTA are based on the pairwise comparison process undertaken by the team of experts. On the other hand, the BN are included for illustrative purposes to emphasize versatility of the selection methodology. The priority vectors are derived from the limit supermatrices depicted, e.g. Table 4.

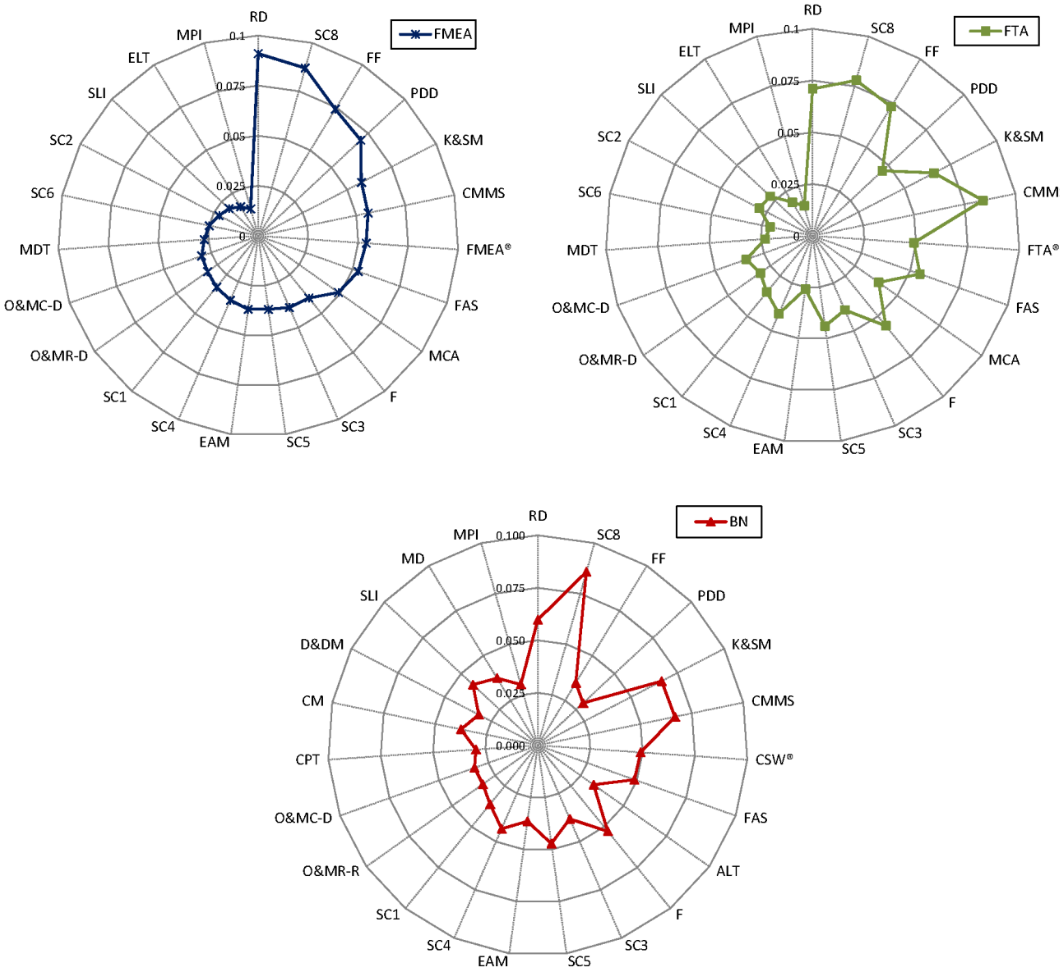

Figure 4. Comparison of the limit priorities for the FMEA, FTA and BN

From the results, the following conclusions can be drawn. For the FMEA technique, the decision element 'reliability database', with a weight of 0.091, is perceived as the important requirement. While this may seem strange given the subjectivity of the classic FMEA, recent research suggests a shift towards use of quantitative FMEA techniques. In fact, the classic FMEA is perceived as cumbersome given time and manpower resource requirements. These concerns are partly addressed by quantitative FMEA approaches where the risk metrics, e.g. probability of failure are derived from equipment reliability data. Moreover, the failure consequences, i.e. in terms of cost, may also be derived from repair cost information, e.g. spare part usage. This negates the need for subjective estimates.

Further, to aid in decision support, the decision element 'process description diagrams' is viewed as an important selection criterion for FMEA. The diagrams assist decision makers' map out critical assets and often an important first step in the risk assessment process. Moreover, 'personnel skills' and 'personnel skills matrix' are perceived as important which is intuitive given the necessary expertise needed for applying FMEA. On the other hand, several elements relevant to the classic FMEA are assigned low priorities. For instance, the decision elements, 'multi-disciplinary teams', 'facilitators' and 'expert elicitation techniques' are ranked lowly. This may be attributed to the perception that diverting manpower resources for performing the classic FMEA approach is disruptive to work activities and consumes time. This agrees with several authors, e.g. Braaksma et al. (2013) where the classic FMEA is cited as one-off exercise and rarely repetitive. As a result, maintenance decisions are seldom linked to output of the FMEA process.

For the FTA technique, the selection criterion 'computerized maintenance management system' is perceived as the most important. This is attributed to the fact that FTA is largely a statistical approach, thus relies on reliability data. The CMMS performs an important role in deriving such data, mainly through generating maintenance work orders. Such orders specify the type of failure, spare part usage and associated downtime. Moreover, the CMMS provides a platform for storing data in 'reliability databases'. To facilitate reliability analysis, 'failure functions', 'personnel skills' and 'knowledge/skills matrix' are perceived as important selection criterion. The importance of PDD for mapping system dependability is underscored in FTA. Here, the PDD provides a crucial decision support tool for mapping hierarchical system failure dependencies, often, technical or logical. The dependencies here differ from the ANP methodology in that, the FTA models system dependability in hierarchical form; the top representing the system failure event and at the bottom, component failure events.

To illustrate the practical application and recommendation for use of the proposed selection framework, two industrial cases are selected for discussion.

6 Illustrative industrial application of the selection framework

6.1 Application in the process industry

The first illustrative case draws from the authors' knowledge of the European process industries and complemented by multiple empirical studies (Braaksma et al., 2013; Muchiri et al., 2010; Pinjala et al., 2006; Veldman et al., 2011). The studies investigate common postulates related to equipment maintenance in the process industries. The studies evaluates postulates postulates regarding the practical use of the FMEA, maintenance performance measurement, relationship between business and maintenance strategy, and condition based maintenance. Although the postulates differ, the empirical studies yield intereresting insights on competencies embedded in the process industries and linked to the selection framework discussed in this article. Table 5 summarises the cited competencies and embeddedness based on the level of support for the particular postulate.

From the summary, several postulates of interest to the selection framework are mentioned as supported and thus embedded in the process industries. These include the availability of plant registers, failure mode identification registers, custom spreadsheets, maintenance management systems, failure databases, highly skilled workforce, and use of quantitative performance measures. The latter, i.e. quantitative performance measures, e.g. time to failure (TTF) forms the basis for deriving statistical models for failure analysis. On the other hand, competencies such as the level of team work/cohesion is mentioned as supported to a limited extent.

The summary highlights simmilarities between competencies embedded in the process industry and those depicted in the proposed selection framework. As such, the competencies cited in the studies are comparable to the prioritised selection criteria presented in this article.

Here, we assume that competencies supported by postulates are weighted highly compared to competencies with limited support. The reader will recall that competencies perceived by experts as critical for applying the quantitative FMEA (Q-FMEA) include reliability databases, personnel skills, statistical models and CMMS. Moreover, with the exception of functional analysis statements (FAS), the aforementioned competencies also apply for FTA.

Thus, comparing the prioritised competencies derived from the ANP process to competencies supported by empirical evidence, the Q-FMEA and FTA may be recommended for use in the process industries. However, this depends on several aspects. Firstly, failure data management is mentioned as an important limitation. This is attributed to low levels of intergration between asset failure related databases. Often in practise, failure related information are stored in separate databases and seldom linked. For instance, information related to equipment failure mode is stored separately to consequence related information, e.g. spare parts usage or production loss. As such, deriving maintenance cost models can be problematic. With regards to applying FTA, caution is urged given challenges related to analysing complex systems. In essence, analysing systems with multiple depedencies between components or failure events is not straightforward and is computationally difficult. The Q-FMEA simplifies quantitative analysis by assuming each failure mode as independent.

Although mentioned as a popular technique, applying the classical FMEA in the process industry is limited by several prioritised competencies. These include low multi-disciplinary cohesion between the maintenance and operation function, the need for facilitation and ad-hoc RCM process. These competencies are not supported by empirical evidence as intrinsic in the process industries. As such, the classic FMEA is not recommended for use by firms in the process industries.

6.2 Application for an automated guided vehicle (AGV) assembler

The second illustrative case concerns a European automated guided vehicle (AGV) assembler. The firm difers from the process industries in several aspects, e.g. nature of business operations, staffing pattern and the importance attached to maintenance (Veldman et al., 2011). In comparison to firms in the process industry, the assember has a modest though, highly skilled workforce. The firm assembles the vehicles using modular components sourced from contracted manufacturers. Once sold, vehicle maintenance beyond the warranty period is the clients responsibility. However, clients have the option of sub-contracting maintenance services to the AGV assembler. On the other hand, AGV failure within the warranty period is largely the assembler's responsibility, thus neccesitating risk mitigation.

Deducing the firms' competencies, the assembler maintains databases for AGV failure and spare part inventory. Often, the databases are vaguely structured and limited to vehicle failure occurrences within the warranty period. Moreover, precise records of vehicle failure modes are lacking. The firm lacks CMMS, but rather implements a condition monitoring system for tracking the client AGV's. Here, trend analysis is the predominant diagnostic approach. The use of statistical models for failure analysis and quantifying asset failure cost is unclear. This includes the use of reliability models, e.g. time to failure (TTF) or time to repair (TTR). In addition, assembly manuals are maintained, often for use in the AGV assembly process. In terms of team work, the AGV assembly and maintenance divisions operate autonomously. Time pressure is also mentioned as an important limitation in relation to performing team tasks.

Based on the firm's competency, deploying a specific risk assessment technique is not straightforward. For instance, the classical FMEA is limited with regards to competencies, e.g. low team cohesion, facilitation and time pressure constraints. This is largely due to the

Table 5: Summary of selection competencies for the process industries

Cited study	Competencies mentioned	Level of support for postulate
Braaksma et al. (2013)	(i) Availability of plant and maintenance registers for mapping critical assets.	(i) Supported
	(ii) In-house expert knowledge on equipment function and functional failures.	(ii) Supported
	(iii) Failure mode identification registers and/or reports.	(iii) Supported
	(iv) Use of custom spreadsheet for FMEA.	(iv) Supported
	(v) Use of structured RCM methodology and multi-disciplinary teams.	(v) Not supported
	(vi) Use of maintenance management system, e.g. SAP-ERP, CMMS.	(vi) Supported
	(vii) Availability of reliability and equipment performance databases.	(vii) Supported
Muchiri et al. (2010)	(i) Use of quantitative performance measures (e.g. reliability, availability, time to failure (TTF).	(i) Supported
	(ii) Highly skilled maintenance personnel.	(ii) Supported
	(iii) Use of maintenance management systems.	(iii) Supported
	(iv) Availability of reliability and equipment performance databases.	(iv) Supported
	(v) Use of predictive maintenance strategies.	(v) Limited support
Pinjala et al. (2006)	(i) Use of predictive maintenance strategies.	(i) Limited support
	(ii) Highly skilled maintenance personnel.	(ii) Supported
	(iii) High level of teamwork between operation and maintenance staff.	(iii) Limited support
	(iv) Use of maintenance management systems.	(iv) Supported
	(v) Use of quantitative performance measures.	(v) Supported
	(vi) Availability of reliability databases and equipment maintenance records.	(vi) Supported
Veldman et al. (2011)	(i) Use of analytical and statistical models for quantifying failure.	(i) Limited support
	(ii) Use of maintenance management systems.	(ii) Supported
	(iii) Highly skilled maintenance personnel.	(iii) Supported
	(iv) Follow procedures for executing maintenance programs.	(iv) Not supported
	(v) Sufficient domain knowledge for managing maintenance programs.	(v) Limited support

divisional autonomy in the firm. Although assembly manuals are used, the manuals are limited to the assembly process and seldom specify critical equipment failure information, e.g. failure mode type. Nonetheless, availability of quantitative equipment information points to feasible application of quantitative risk assessment technique, e.g. the Q-FMEA. However, given that the information only specifies the equipment condition, several enhancements to the data structure is necessary. These include possible inclusion of information related to the type of failure mode, time to failure, time to repair, spare part usage, or production loss attributed to equipment failure. Inclusion of this information would assist in the derivation of reliability and maintenance cost models. Other competencies, e.g. highly skilled personnel appear embedded in the firm. This is evidenced by the presence of reliability engineers. From the prioritized competencies, personnel skills are weighted as important requisite for applying quantitative risk assessment techniques. Other important areas of improvement include integrating failure related databases, a limitation also noted for firms in the process industry. Integrated databases will ensure that the failure modes are linked to the respective failure consequences i.e. cost of failure.

To conclude, the two application cases illustrate the possible steps that firms can follow to select appropriate technique based on the firms' intrinsic competencies. The cases illustrate the versatility of the proposed selection framework with respect providing decision support to firms with varying business or operation context. Moreover, the comparison process discussed in the cases assumes the instance where the ANP process is externalized, i.e. performed by experts not specifically linked to the two firms. However, the ANP prioritization is also applicable in-house provided there is sufficient tacit knowledge regarding use of the specific risk assessment technique. Preferably, the selection criteria discussed in Section 5.1 may guide the ANP process.

7. A general guideline for selecting appropriate risk assessment technique

From the illustrative cases discussed, a general guideline for selecting appropriate techniques may be deduced. The guideline is included in Appendix A and consists of 5 key steps:

1. In Step 1, the firm identifies organizational competencies necessary for performing risk assessment. The competencies are linked to steps enumerated in the ISO 31000 standard and the guideline suggested in Section 4 is quite useful for the derivation process.
2. In Step 2, firms compare the firms intrinsic versus competencies prioritized by external experts. Part of reason for the external comparison may include lack of essential expertise for the ANP prioritization process. Examples may include limited knowledge regarding use of specific risk assessment techniques. The application cases illustrate how firms can perform Step 2.
3. In Step 3, competencies identified in Step 1 are prioritized in-house. Here, the steps necessary for establishing the team of experts, ANP problem formulation and prioritization process are followed. Details for Step 3 are enumerated in Section 5.
4. Step 4 depicts the comparison process between the firms' intrinsic versus competencies prioritized through ANP process. The appropriate technique is one where the firms' intrinsic competencies weigh highly compared to the prioritized competencies for the specific technique, e.g. as expounded in the illustrative use cases. The competencies depicted in Step 4 (Appendix A) are summarized for brevity. Thus depending on the competency level, a firm may select a specific technique for risk assessment. This is depicted by the multiple arrows originating from the decision module 'competency level'.

5. Step 5 depicts the enhancement of specific competencies in instances where the firm lacks sufficient competencies or opts to apply a better and perhaps more complex technique. The improvement process is illustrated by the feedback loops from decision modules depicted in Step 4. The enhancement process is also described in the use case studies.

8. Discussion and managerial implications

In this article, a conceptual methodology for selecting risk assessment techniques in the asset maintenance domain is proposed. The methodology follows a deductive process for deriving selection criteria based on the ISO 31000:2009 standard. The selection criteria are generic, thus generalizable to alternative techniques applicable in asset maintenance. Moreover, the relative importance of each criterion varies depending on the type of technique applied and for this reason the ANP methodology is applied for the prioritization process. The ANP process incorporates the judgment and opinion of domain experts knowledgeable on specific techniques. As such, the proposed framework is viewed as an important decision support tool for maintenance practitioners not well-versed with the use of different risk assessment techniques. Here, the selection framework acts as an important reference point, allowing firms to compare intrinsic versus competencies prioritized by experts using the ANP process. The selection methodology is illustrated in two case studies, the first concerning firms in the European process industry and the second, an automated guided vehicle (AGV) assembler.

The illustrative case for the process industries indicates that based on intrinsic competencies supported by empirical evidence, applying quantitative techniques, e.g. the Q-FMEA and/or FTA seems plausible. Nonetheless, several weaknesses are highlighted with respect to applying quantitative techniques in the process industry. These include low level of system integration between equipment failure related databases. For the second firm, the intrinsic competencies also suggest possible use of quantitative techniques, e.g. the Q-FMEA. However, the absence of a robust failure data management system is viewed as an important limitation. From the case studies, one can conclude that selecting a technique is case specific and largely influenced by the extent the intrinsic capabilities are embedded in the organization. As a result, recommendations for use are also case specific and not generalizable across domains. This aspect underscores the danger of selecting techniques prior to considering the firm's intrinsic competencies as often the case in practice.

9. Conclusion

This paper proposes a methodology for selecting appropriate risk assessment techniques in the context of maintenance decision making. Such techniques perform critical decision support role and include the Failure Mode and Effect Analysis, Fault Tree Analysis and the Bayesian Network. Despite the important role the techniques perform in maintenance decision making, a structured methodology for selecting appropriate techniques in practice is missing in literature.

In the proposed methodology, the criteria necessary for applying specific risk assessment techniques are derived taking into account intrinsic organizational competencies necessary for deploying specific techniques. Moreover, the derived criteria are linked, on the one hand, to the techniques, and on the other hand, the risk assessment process outlined in the ISO 31000:2009 standard. The methodology incorporates the Analytic Network Process (ANP) methodology for prioritizing the selection criteria taking into account the opinion of domain experts knowledgeable on the specific techniques. The selection methodology forms the basis for comparing the firms' intrinsic competencies relative to prioritized competencies, thus presenting maintenance practitioners with a plausible selection framework.

Future work will consider extending the methodology to alternative (and more complex) techniques. Incorporating additional techniques provides a means for documenting tacit knowledge with respect to applying different risk assessment techniques. Moreover, this may yield a robust decision support tool for selecting suitable techniques in the maintenance decision making domain.

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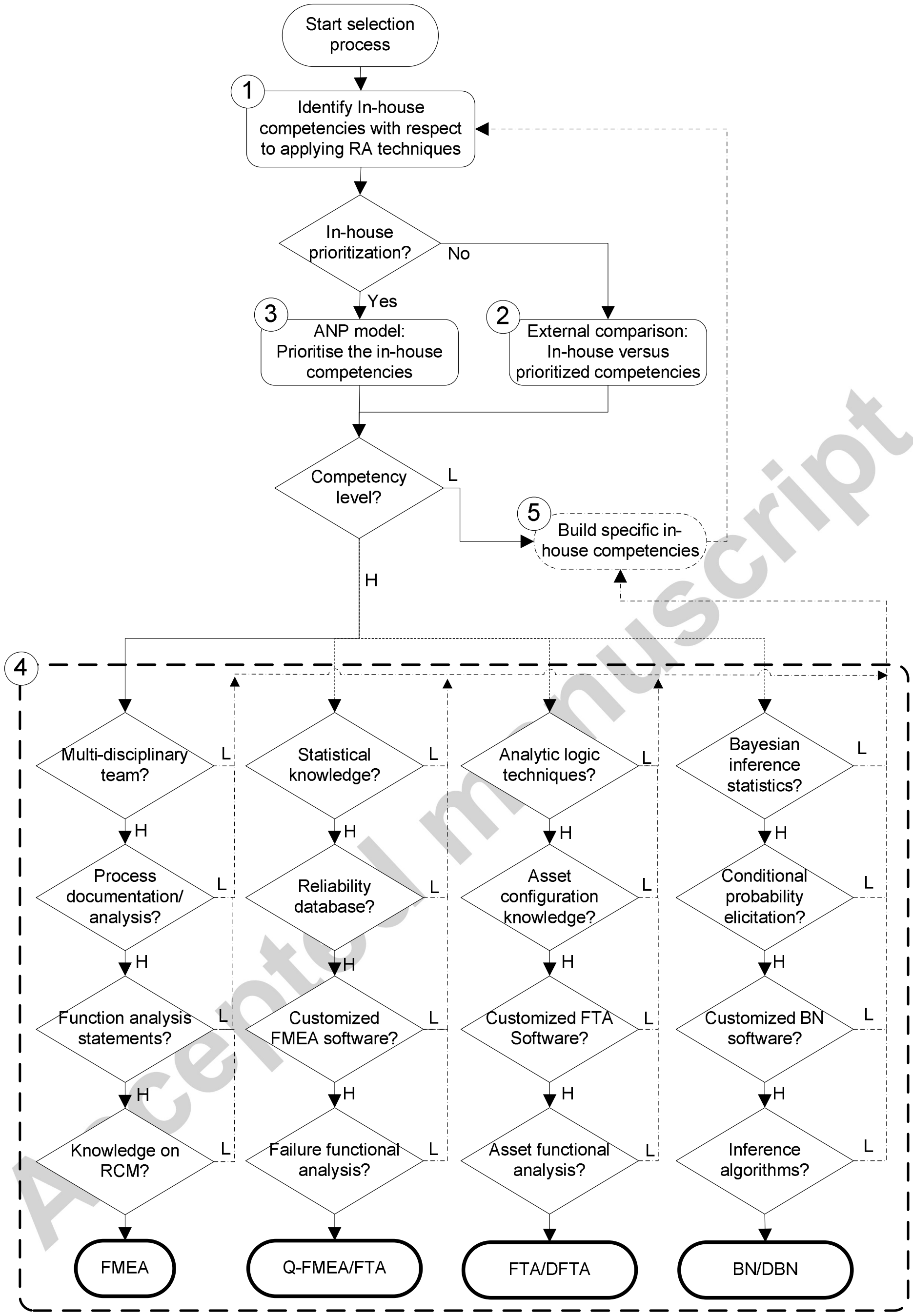
Appendix A: General guideline for selecting appropriate risk assessment techniques.



FMEA: Failure Mode and Effect Analysis
Q - FMEA: Quantitative Failure Mode and Effect Analysis
BN: Bayesian Network
H: High

FTA: Fault Tree Analysis
DFTA: Dynamic Fault Tree Analysis
DBN: Dynamic Bayesian Network
L: Low

Table 4: Limit supermatrix for FMEA selection.

	FMEA	SC 1	SC 2	SC 3	SC 4	SC 5	SC 6	SC 8	CMMS	EAM	FMEA®	PDD
FMEA	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Software tools (SC 1)	0.033	0.033	0.033	0.033	0.033	0.033	0.033	0.033	0.033	0.033	0.033	0.033
Software modules (SC 2)	0.022	0.022	0.022	0.022	0.022	0.022	0.022	0.022	0.022	0.022	0.022	0.022
Decision support tools (SC 3)	0.039	0.039	0.039	0.039	0.039	0.039	0.039	0.039	0.039	0.039	0.039	0.039
Data collection schemes (SC 4)	0.035	0.035	0.035	0.035	0.035	0.035	0.035	0.035	0.035	0.035	0.035	0.035
Statistical models (SC 5)	0.037	0.037	0.037	0.037	0.037	0.037	0.037	0.037	0.037	0.037	0.037	0.037
Performance measurement (SC 6)	0.025	0.025	0.025	0.025	0.025	0.025	0.025	0.025	0.025	0.025	0.025	0.025
Personnel skills (SC 8)	0.087	0.087	0.087	0.087	0.087	0.087	0.087	0.087	0.087	0.087	0.087	0.087
Computerized maintenance management (CMMS)	0.056	0.056	0.056	0.056	0.056	0.056	0.056	0.056	0.056	0.056	0.056	0.056
Enterprise asset management (EAM)	0.037	0.037	0.037	0.037	0.037	0.037	0.037	0.037	0.037	0.037	0.037	0.037
Customized FMEA software (FMEA®)	0.054	0.054	0.054	0.054	0.054	0.054	0.054	0.054	0.054	0.054	0.054	0.054
Process description diagrams (PDD)	0.070	0.070	0.070	0.070	0.070	0.070	0.070	0.070	0.070	0.070	0.070	0.070
Operation and maintenance records (O&M-R)	0.031	0.031	0.031	0.031	0.031	0.031	0.031	0.031	0.031	0.031	0.031	0.031
Reliability database (RD)	0.091	0.091	0.091	0.091	0.091	0.091	0.091	0.091	0.091	0.091	0.091	0.091
Operation and maintenance cost database (O&MC-D)	0.030	0.030	0.030	0.030	0.030	0.030	0.030	0.030	0.030	0.030	0.030	0.030
Failure functions (FF)	0.074	0.074	0.074	0.074	0.074	0.074	0.074	0.074	0.074	0.074	0.074	0.074
Monte Carlo analysis (MC)	0.049	0.049	0.049	0.049	0.049	0.049	0.049	0.049	0.049	0.049	0.049	0.049
Functional analysis statements (FAS)	0.053	0.053	0.053	0.053	0.053	0.053	0.053	0.053	0.053	0.053	0.053	0.053
Maintenance performance indicators (MPI)	0.014	0.014	0.014	0.014	0.014	0.014	0.014	0.014	0.014	0.014	0.014	0.014
Systems loss indicators (SLI)	0.020	0.020	0.020	0.020	0.020	0.020	0.020	0.020	0.020	0.020	0.020	0.020
Facilitator/statistician (s) (F)	0.040	0.040	0.040	0.040	0.040	0.040	0.040	0.040	0.040	0.040	0.040	0.040
Multi-disciplinary teams (MDT)	0.027	0.027	0.027	0.027	0.027	0.027	0.027	0.027	0.027	0.027	0.027	0.027
Expert elicitation techniques (ELT)	0.017	0.017	0.017	0.017	0.017	0.017	0.017	0.017	0.017	0.017	0.017	0.017
Knowledge/skills matrix (K&SM)	0.058	0.058	0.058	0.058	0.058	0.058	0.058	0.058	0.058	0.058	0.058	0.058

Table 4: Limit supermatrix for FMEA selection (continued).

	O&M-R	RD	O&MC-D	FF	MC	FAS	MPI	SLI	F	MDT	ELT	K&SM
FMEA	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Software tools (SC 1)	0.033	0.033	0.033	0.033	0.033	0.033	0.033	0.033	0.033	0.033	0.033	0.033
Software modules (SC 2)	0.022	0.022	0.022	0.022	0.022	0.022	0.022	0.022	0.022	0.022	0.022	0.022
Decision support tools (SC 3)	0.039	0.039	0.039	0.039	0.039	0.039	0.039	0.039	0.039	0.039	0.039	0.039
Data collection schemes (SC 4)	0.035	0.035	0.035	0.035	0.035	0.035	0.035	0.035	0.035	0.035	0.035	0.035
Statistical models (SC 5)	0.037	0.037	0.037	0.037	0.037	0.037	0.037	0.037	0.037	0.037	0.037	0.037
Performance measurement (SC 6)	0.025	0.025	0.025	0.025	0.025	0.025	0.025	0.025	0.025	0.025	0.025	0.025
Personnel skills (SC 8)	0.087	0.087	0.087	0.087	0.087	0.087	0.087	0.087	0.087	0.087	0.087	0.087
Computerized maintenance management (CMMS)	0.056	0.056	0.056	0.056	0.056	0.056	0.056	0.056	0.056	0.056	0.056	0.056
Enterprise asset management (EAM)	0.037	0.037	0.037	0.037	0.037	0.037	0.037	0.037	0.037	0.037	0.037	0.037
Customized FMEA software (FMEA®)	0.054	0.054	0.054	0.054	0.054	0.054	0.054	0.054	0.054	0.054	0.054	0.054
Process description diagrams (PDD)	0.070	0.070	0.070	0.070	0.070	0.070	0.070	0.070	0.070	0.070	0.070	0.070
Operation and maintenance records (O&M-R)	0.031	0.031	0.031	0.031	0.031	0.031	0.031	0.031	0.031	0.031	0.031	0.031
Reliability database (RD)	0.091	0.091	0.091	0.091	0.091	0.091	0.091	0.091	0.091	0.091	0.091	0.091
Operation and maintenance cost database (O&MC-D)	0.030	0.030	0.030	0.030	0.030	0.030	0.030	0.030	0.030	0.030	0.030	0.030
Failure functions (FF)	0.074	0.074	0.074	0.074	0.074	0.074	0.074	0.074	0.074	0.074	0.074	0.074
Monte Carlo analysis (MC)	0.049	0.049	0.049	0.049	0.049	0.049	0.049	0.049	0.049	0.049	0.049	0.049
Functional analysis statements (FAS)	0.053	0.053	0.053	0.053	0.053	0.053	0.053	0.053	0.053	0.053	0.053	0.053
Maintenance performance indicators (MPI)	0.014	0.014	0.014	0.014	0.014	0.014	0.014	0.014	0.014	0.014	0.014	0.014
Systems loss indicators (SLI)	0.020	0.020	0.020	0.020	0.020	0.020	0.020	0.020	0.020	0.020	0.020	0.020
Facilitator/statistician (s) (F)	0.040	0.040	0.040	0.040	0.040	0.040	0.040	0.040	0.040	0.040	0.040	0.040

Multi-disciplinary teams (MDT)	0.027	0.027	0.027	0.027	0.027	0.027	0.027	0.027	0.027	0.027	0.027	0.027
Expert elicitation techniques (ELT)	0.017	0.017	0.017	0.017	0.017	0.017	0.017	0.017	0.017	0.017	0.017	0.017
Knowledge/skills matrix (K&SM)	0.058	0.058	0.058	0.058	0.058	0.058	0.058	0.058	0.058	0.058	0.058	0.058

Table 5: Summary of selection competencies for the process industries

Cited study	Competencies mentioned	Level of support for postulate
Braaksma et al. (2013)	(i) Availability of plant and maintenance registers for mapping critical assets. (ii) In-house expert knowledge on equipment function and functional failures. (iii) Failure mode identification registers and/or reports. (iv) Use of custom spreadsheet for FMEA. (v) Use of structured RCM methodology and multi-disciplinary teams. (vi) Use of maintenance management system, e.g. SAP-ERP, CMMS. (vii) Availability of reliability and equipment performance databases.	(i) Supported (ii) Supported (iii) Supported (iv) Supported (v) Not supported (vi) Supported (vii) Supported
Muchiri et al. (2010)	(i) Use of quantitative performance measures (e.g. reliability, availability, time to failure (TTF). (ii) Highly skilled maintenance personnel. (iii) Use of maintenance management systems. (iv) Availability of reliability and equipment performance databases. (v) Use of predictive maintenance strategies.	(i) Supported (ii) Supported (iii) Supported (iv) Supported (v) Limited support
Pinjala et al. (2006)	(i) Use of predictive maintenance strategies. (ii) Highly skilled maintenance personnel. (iii) High level of teamwork between operation and maintenance staff. (iv) Use of maintenance management systems. (v) Use of quantitative performance measures.	(i) Limited support (ii) Supported (iii) Limited support (iv) Supported (v) Supported (vi) Supported

	(vi) Availability of reliability databases and equipment maintenance records.	
Veldman et al. (2011)	(i) Use of analytical and statistical models for quantifying failure. (ii) Use of maintenance management systems. (iii) Highly skilled maintenance personnel. (iv) Follow procedures for executing maintenance programs. (v) Sufficient domain knowledge for managing maintenance programs.	(i) Limited support (ii) Supported (iii) Supported (iv) Not supported (v) Limited support