Uncertainty Analysis in Product Service System

Bayesian Network Modelling for Availability Contract

by

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Abstract

There is an emerging trend of manufacturing companies offering combined products and services to customers as integrated solutions. Availability contracts are an apt instance of such offerings, where product use is guaranteed to customer and is enforced by incentive-penalty schemes. Uncertainties in such an industry setting, where all stakeholders are striving to achieve their respective performance goals and at the same time collaborating intensively, is increased. Understanding through-life uncertainties and their impact on cost is critical to ensure sustainability and profitability of the industries offering such solutions.

In an effort to address this challenge, the aim of this research study is to provide an approach for the analysis of uncertainties in Product Service System (PSS) delivered in business-to-business application by specifying a procedure to identify, characterise and model uncertainties with an emphasis to provide decision support and prioritisation of key uncertainties affecting the performance outcomes. The thesis presents a literature review in research areas which are at the interface of topics such as uncertainty, PSS and availability contracts. From this seven requirements that are vital to enhance the understanding and quantification of uncertainties in Product Service System are drawn. These requirements are synthesised into a conceptual uncertainty framework. The framework prescribes four elements, which include identifying a set of uncertainties, discerning the relationships between uncertainties, tools and techniques to treat uncertainties and finally, results that could ease uncertainty management and analysis efforts.

The conceptual uncertainty framework was applied to an industry case study in availability contracts, where each of the four elements was realised. This application phase of the research included the identification of uncertainties in PSS, development of a multi-layer uncertainty classification, deriving the structure of Bayesian Network and finally, evaluation and validation of the Bayesian Network.

The findings suggest that understanding uncertainties from a system perspective is essential to capture the network aspect of PSS. This network comprises of several stakeholders, where there is increased flux of information and material flows and this could be effectively represented using Bayesian Networks.

Dedication

To Shivani Ben and Samanvitha

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Abbreviations

BN – Bayesian Network

BTG – Bayes Table Generator

CADMID - Concept, Assessment, Development, Manufacture, In-Service, Disposal

CATA - Costing for Avionic Through-life Availability

CDF - Cumulative Density Function

CP - Conditional Probability

CPT – Conditional Probability Tables

EQ - Equipment Readiness

FRACAS - Failure Reporting Analysis & Corrective Action System

IDEF - Integration DEFinition

ITAR - International Traffic in Arms Regulations

MHDD - Multifunctional Head Down Display

MoD - Ministry of Defence (UK)

NFF - No Fault Found

OEM - Original Equipment Manufacturer

PDF – Probability Density Function

PSS - Product Service System

RAF – Royal Air Force

TT - Turnaround Time

1 Introduction

Product Service System (PSS) in business-to-business application are an innovative business model for engineering industries, who offer it as market proposition that goes beyond the traditional functionality of a product by including additional services (Steven and Richter, 2010; Baines et.al. 2007). This emerging trend of industries providing a combined offering of services and products arise due to many reasons. One of the reasons is to create a differentiation factor for manufacturers to compete with other competitors who offer similar products (Aurich et.al. 2006) and overcome the saturated product market (Williams, 2006), resulting in competitive advantage because services cannot be replicated easily (Shostack, 1977). Secondly, shrinkage in the revenue generated by selling products has led to the recognition that providing services to their customers is where the real money is (Wise and Baumgartner, 1999). This combined offering of product and services provided by the manufacturers has profound impact and requires transformation of people, information and equipment (Ng et.al. 2011). These offerings require the servitising manufacturer to design new contracts which address the sharing of responsibilities and risks arising due to the provision of service (Vladimirova et.al. 2011). Availability contracts are one such type of service contracts, where the aim is to provide operational availability through an integrated and effective support solution, generally by an industry or a combination of industries and government as the customer (Hockley et.al. 2011). Customers also face dilemma on the acceptance of PSS because of high uncertainty surrounding the eventual cost of purchasing PSS as it is difficult to evaluate the costs of a given product for the duration of its life cycle, uncertainty in the decision on the type of provision that is most advantageous and uncertainty on the expectations of performance from PSS provision (Catulli, 2012). The PSS provider has to assure resolving these uncertainties but these uncertainties are also inflicted on the PSS provider. Examples of PSS exist in business markets, such as Xerox leasing its print machines, which includes services such as recovering and remanufacturing waste consumables and the machines themselves (Shelton, 2009). Another example, is Rolls Royce “loaning” aircraft engines which is combined with service bundle that includes maintenance, repair and invoicing customers for mileage flown and power delivered (Shelton, 2009).

1.1 Business Context

Industrial Product Service System (IPS^2), technical PSS and functional products are some terms used for PSS in business-to-business applications (Roy and Cheruvu, 2008; Meier et.al, 2010;

Parida et.al. 2013). The term PSS is usually used in the consumer market context and IPS[2] is related to problem solution solving of business-to-business market issues (Sadek and Koster, 2011). In this research, the term PSS is used to refer to business-to-business applications because of its generic outlook and the term showcases it's meaning right away to even a non-expert reader.

PSS is mainly focussed on providing customer adjusted solutions (Meier et.al. 2010). This means that a high quality product is not the primary interest of the customer, but the functionality that the product provides in a reliable and efficient manner is the factor that appeals the customer most. Although PSS has been researched extensively, there is limited application of PSS in industry and at the academic level, PSS have not yet been studied and shaped for practical applications (Mont, 2001). However, there are developments from the concept of PSS to practical implementation in real-world business, especially in defence sector, where contracting for availability and capability is rapidly gaining momentum (Hockley et.al. 2011). The concept of PSS is a special case of servitisation, which started in Northern Europe in the late 1990s (Baines et.al. 2007). On the other hand, availability contracts are described as a special case of PSS (Datta and Roy 2010). Figure 1 presents this evolution from concept to application of PSS.

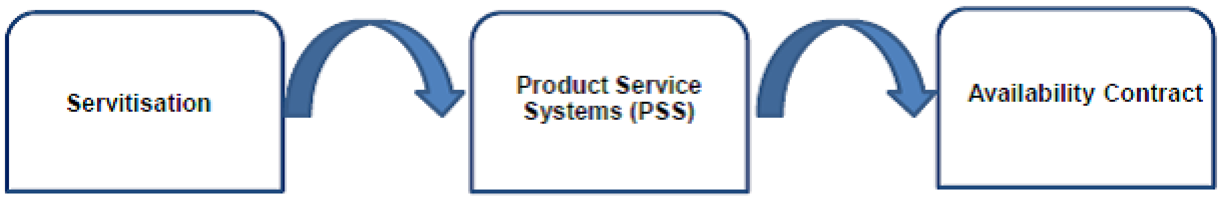


Figure 1: Concept to Application (Narayana et.al. 2012)

'TotalCare®' package is an example of PSS offered to airliners by aircraft engine manufacturer Rolls-Royce, where offering is '*power-by-the-hour*' availability contracts rather than transferring ownership of the gas turbine engine (Harrison, 2006). Chirumalla et.al. (2013) illustrate PSS dimension of 'TotalCare®' package, as a composition of product, services, networks and infrastructures (Mont, 2004). *Product* is the Aircraft engine to be sold as '*power-by-the-hour*'. *Services* include maintenance, repair, overhaul, disposal, engine installation in the aircraft, spare parts provision, service manuals provision, availability of service technicians at customer sites and airports and service training. *Networks* represent relation between engine provider, suppliers, service providers, recyclers and third business partners in order to deliver total solution to customer. *Infrastructure* consists of service centres across airports, logistics and distribution channels, extended enterprise IT architecture, knowledge management systems. The enlarged network of stakeholders for 'TotalCare®' package from knowledge sharing perspective (Chirumalla et.al. 2013) is shown in Figure 2.

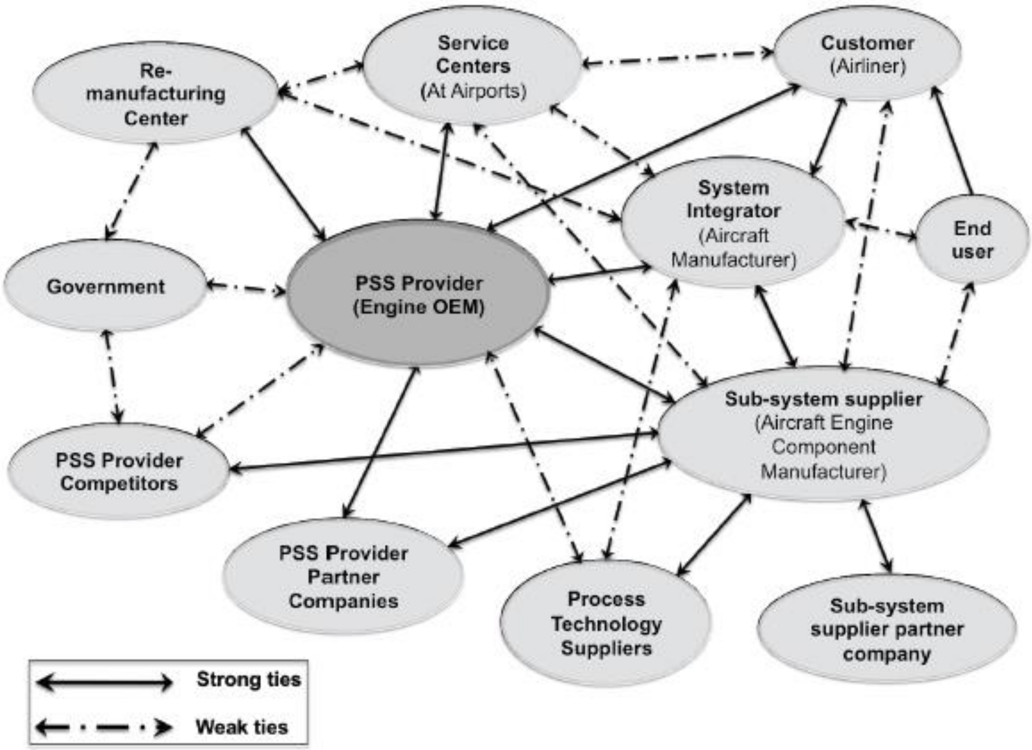


Figure 2: Network Aspect of PSS Dimension (Chirumalla et.al. 2013)

Networks facilitate communication and interaction among stakeholders and act as mechanisms for creating value and for sharing information and knowledge as well as for creating awareness of sustainability agendas and goals (Durugbo and Riedel, 2013; Chirumalla et.al. 2013; Wang and Durugbo, 2013). And researchers generally agree that networks are critical to achieving the goals of PSS in business-to-business application (Wang and Durugbo, 2013). The network dimension of PSS enforces joint decision making by industries under uncertainty, which could have exogenous implications that extend beyond the individual industry to supply chains or endogenous implications faced within the industry and hence, it is imperative that partnering stakeholders augment their understanding of uncertainty issue in PSS delivery and transitions to service networks (Wang and Durugbo, 2013).

1.2 Research Project

This research is part of the parent project "Costing for Avionic Through-Life Availability" (CATA) funded by the Innovative electronics Manufacturing Research Centre (IeMRC). CATA is motivated by the momentum gained in availability-based contracts and in particular the five-year £450M Typhoon Availability Service (TAS) contract awarded in 2009 (Thenent, 2014). TAS was a partnering arrangement between BAE Systems and the UK Ministry of Defence (MoD), Defence Equipment and Support (DE&S) organisation in close cooperation with the Royal Air Force (RAF) to maintain and support the RAF fleet of Typhoon aircraft. The aim of CATA is a proof of concept of a cost model that supports informed decision making in availability-type contracts. The research conducted in CATA follows four threads of research, as shown in Figure 3.

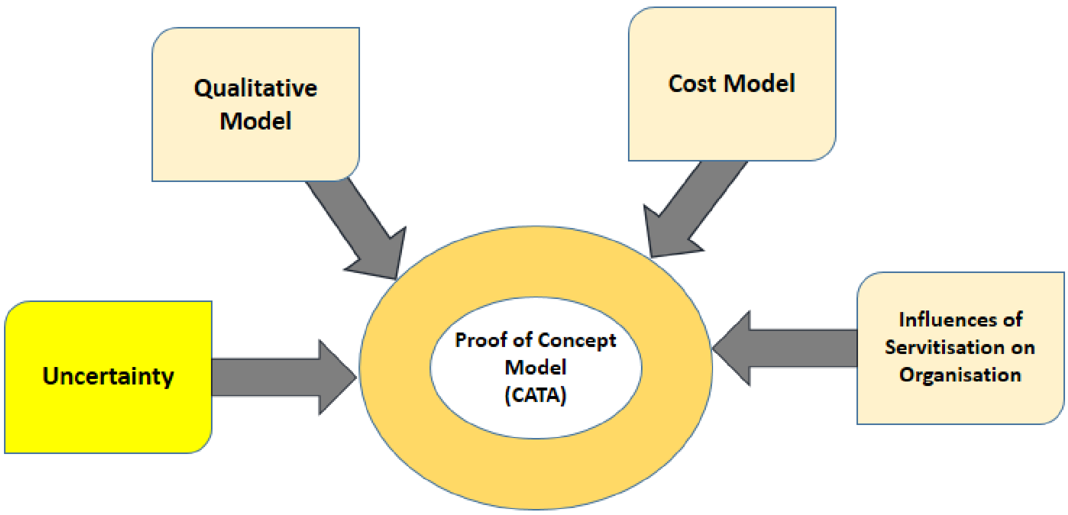


Figure 3: Research conducted in CATA Project (Thenent, 2014)

The uncertainty strand of research is presented in this thesis, where understanding and modelling of uncertainty is looked into. The term uncertainty has been used in subtly different ways in fields ranging from philosophy, statistics, economics, finance, insurance, psychology, engineering to science (Weck et.al. 2007). In this research, we adopt a definition of uncertainty which has been frequently used in the engineering field. Hence, *uncertainty is defined as any deviation from the unachievable ideal of completely deterministic knowledge of the relevant system (Walker et.al. 2003).*

The qualitative model dealt with integrating social and technical aspects in the representation of PSS as a foundation for costing advanced services, in particular avionics availability. The qualitative model is linked to the cost model developed by providing the underlying structure of the model. The last strand of research is about influences of servitisation on the organisation that causes change in responsibilities when organisations are involved in the delivery of availability.

1.3 Research Motivation

A common theme in literature has been addressing significance of services on how they can complement sale or lease of a tangible product and their contribution for the growth and competitive success of manufacturing company (Mathe and Shapiro, 1993), which was in the past neglected (Oliva and Kallenberg, 2003). There has been a surge in research on service especially on forecasting of service cost, however research explicitly addressing uncertainties in service is sparse.

PSS should be developed based on lifecycle thinking (Sundin, 2009). Researchers have observed a change in service offering from basic to more complex service offering for different stages in the lifecycle and different types of long-term solutions (Rabetino et.al. 2015). Concept, Assessment, Demonstration, Manufacture, In-service and Disposal (CADMID) cycle is the representation of the different stages of lifecycle of a typical PSS project within defence industry (Johnsen et.al. 2009; Bankole et.al. 2011). Figure 4 shows the graphical representation of the cost incurred during the various phases of CADMID cycle, where testing with prototypes and manufacturing phases incur high costs, however the in-service phase can stretch to several decades with higher costs incurred (Johnsen et.al. 2009). Operating and support costs form a significant proportion (up to 80%) of the total lifecycle cost (Asiedu and Gu, 1998).

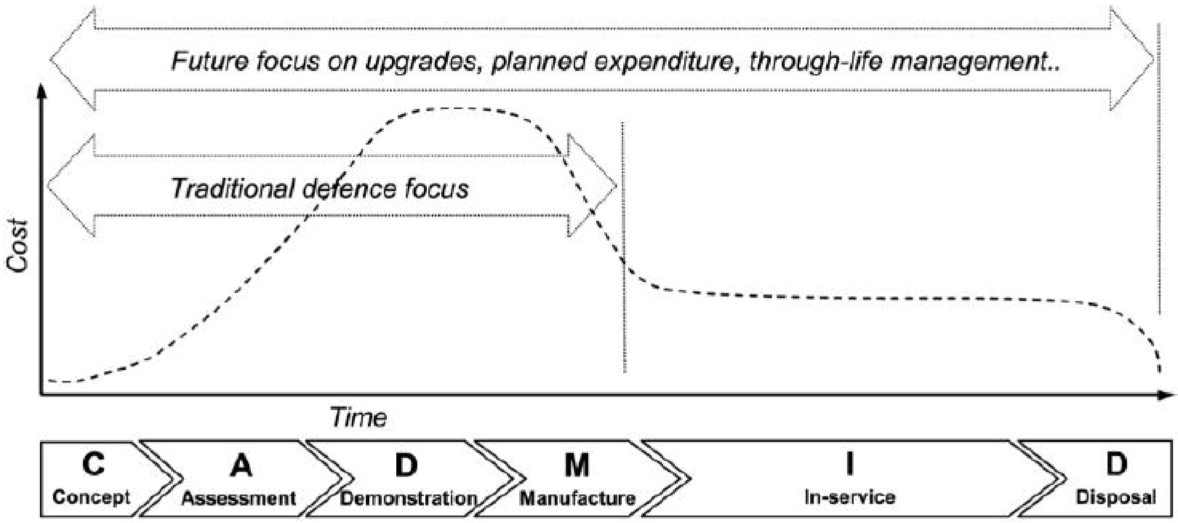


Figure 4: Typical Cost Profile during the CADMID Cycle (Johnsen et.al. 2009)

Hence, it can be said that dealing with uncertainty in the in-service phase is most crucial, because the maintenance cost can add up to several times the initial investments, as mentioned before and also, the maintenance activities have a significant impact on the operational availability of the equipment itself (Mulder et.al. 2013). Service network, complex long-life equipment and complex engineering services are the main drivers of uncertainty in PSS delivered in business-to-business application (Demeter et.al. 2011; Oliva and Kallenberg, 2003; Zhang and Zhang, 2014). The quality of information flow and knowledge across the value service network during the period of a contract creates issues in the accommodation of operational requirements propels uncertainty associated to services provided (Roy, 2011). Typically B2B availability contracts require the combined capability and resources from several companies in the upstream and downstream value chains. Therefore the development and delivery of PSS in business-to-business applications is a complex assignment involving long-term commitment with higher levels of risks and responsibilities (Parida et.al. 2013).

McManus and Hastings (2005) suggest lack of knowledge, lack of definition, statistically characterised variables, known unknowns and unknown unknowns as the uncertainties faced during the design of complex equipment. Some examples for the above uncertainties are mentioned below (McManus and Hastings, 2005). Lack of knowledge could be not knowing the fatigue properties of 7075-T6 aluminium, which could be obtained or a test program designed at a later stage. Lack of definition could be when rivet spacing's are specified for a

High Speed Civil Transport (HSCT) but not fuselage materials or markets at the time of its cancellation. Statistically characterised (random) variables could include fatigue properties of 7075-T6 aluminium and most environmental variables (weather, space environment, etc.). Known unknowns are future budgets, future adversaries, the performance of new technologies, whereas Unknown Unknowns for example, could be large civil engineering structures have very high margins based on the high probability that sometime in 100 and more years something strange will happen. In service delivery, examples of uncertainties could be lack of information because suppliers not provide information on anticipated late deliveries, human error while diagnosing faults in equipment, ambiguity in terminologies used by service personnel across different departments and organisations, customers perception of quality of service provided (Grote, 2009; Catulli, 2012; Márquez, 2007). As PSS are integrated product and service offerings that deliver superior customer value in industrial applications by mutually determined planning, development, delivery and use of product and service shares (Lagemann and Meier, 2014), the uncertainties arising during design of complex equipment impact the delivery phase, especially with greater dependency on uncertainties associated to equipment reliability and also driven by the prolonged in-service phase of the long-life equipment (Uhlmann et.al. 2011; Johnsen et.al. 2009).

Complex engineering services require simultaneous transformation of information, people as well as materials and equipment (Ng et al. 2009). This intensity of transformation to meet the required performance measures itself entails increasing uncertainties, which needs to be dealt with by all the stakeholders involved in the delivery of PSS in business-to-business applications. For example, introduction of a new advanced equipment suitable for PSS offering would require transformation of skill set possessed by people in the organisation, due to obsolescence of their skills (Romero-Rojo, 2009). Various uncertainties exist in after-sales service that influence customer satisfaction such as availability of technical services and staff, general attitude and behaviour of technician, response time and repair time, availability of spare parts, price of the service and service contract options (Finke and Hertz, 2011). There is a need to identify all the possible uncertainties in PSS, which is a natural step in order to analyse and manage them. Understanding these uncertainties in greater detail would enable to employ appropriate approaches to treat them. Characteristics of uncertainties could provide cues to the modeller on several modelling decisions, which is not addressed in research. PSS comprises of several uncertainties, where relationships among these uncertainties exist and these relationships among the uncertainties can be used in a given purposeful way for determining unknown states of some uncertainties on the basis of known states of other uncertainties. There is currently lack of modelling technique that captures relationships between uncertainties explicitly in PSS and understand interaction between various sources of uncertainty. PSS is a novel concept that is paving its path towards industry applications and hence, there is lack of data that hinders the luxury of choice of modelling techniques that could be used. Hence, utilising the knowledge of experts who are working towards delivering competitive PSS in business-to-business applications is a potential choice to overcome data obstacles. There is need for a rigorous structured approach towards understanding and quantifying uncertainties in PSS decision problems, in a transparent and effective manner. All these provides the motivation of this research to understand and quantify uncertainties.

1.4 Research Aim and Contribution

The aim of this research study is to provide an approach to analyse uncertainties in PSS delivered in business-to-business application by specifying a procedure to identify, characterise and model uncertainties with an emphasis to provide decision support and prioritisation of key uncertainties affecting the performance outcomes.

The three questions that a modeller and/or decision maker has to know is what are the uncertainties in PSS?, what are the characteristics of these uncertainties? and finally, what is the measure of uncertainty? The argument of this research is that it is not sufficient to find answers to these questions individually but also find the relations between them. It is based on general systems theory, which states that the individual components if examined on their own, do not have any meaning (Sagasti and Mitroff, 1973). Just knowing what the uncertainties are would not be enough to address the uncertainty problem in PSS, similarly knowing the characteristics of uncertain alone would not lead to a holistic solution and likewise knowing the numerical value associated to the uncertainty would not be enough. Hence, it is necessary to capture these three outcomes and the relation between these to obtain a solution from a holistic point of view. Traversing from identifying to modelling would result in prioritising key uncertainties as deeper understanding is gained about its characteristics and finally numerically supported by conducting sensitivity analysis of the model. This is represented in Figure 5 below.

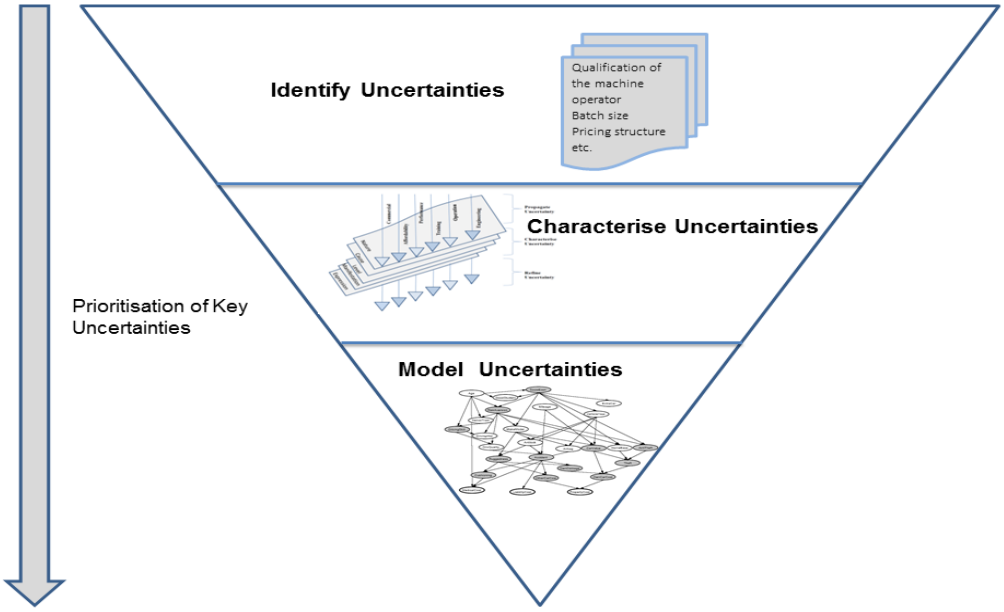


Figure 5: Outcomes of Research Aim

The novel contribution of this research can be summarised in terms of solution to achieve these three outcomes of uncertainty in order to understand and quantify uncertainties in PSS and would lead to the following deliverables:

- **An uncertainty framework to understand and quantify uncertainty**: A conceptual framework which provides an integrated solution in terms of the uncertainties present, their characteristics and modelling approach.
- **A checklist of uncertainties experienced during PSS delivery:** An array of uncertainties resulting from product, service and system dimension of PSS.
- **An uncertainty classification:** A multi-layer uncertainty classification for characterising uncertainties in order to understand them and interpret the characteristics to provide model-based decision support.
- **An uncertainty model to provide decision-support in PSS delivery:** A model that can provide configuration of states of different uncertainties for a desired outcome and hence, providing decision support at strategic and/or operational level that would aid in planning of PSS delivery.

1.5 Research Methodology

This Section on research methodology outlines the research plan mapping research objectives and the research methods employed in the corresponding chapters. This is followed by a discussion of the research phases which synthesises the overall research progress from conceptualisation to validation. The subsequent section presents the research approach adopted in this research, where the interconnection between applied methods in this research project (Tay and Wallis, 2000) within the different research phases is discussed.

1.5.1 Research Objectives

The objectives of this research serve as milestones and guide in the progress towards achieving the research aim. The aim of this research as presented contribute towards an approach to analyse uncertainties in PSS delivered in business-to-business application by specifying a procedure to identify, characterise and model uncertainties with an emphasis to provide decision support and prioritisation of key uncertainties affecting the performance outcomes. The research objectives identified are as follows:

1. To develop a approach to identify uncertainties affecting PSS delivery.
2. To specify and develop a suitable uncertainty classification for uncertainties in PSS delivered in business-to-business application.
3. To define a framework to understand and quantify uncertainties in PSS delivered in business-to-business application.
4. To determine how uncertainties impact on the delivery of PSS in business-to-business application.

These research objectives would aid in achieving the deliverables outlined in Section 1.4. Each objective emphasis on the developing an approach in order to obtain the required deliverables. Achieving objective one would result in a checklist of uncertainties. Similarly, achieving Objective two would result in a multi-layer uncertainty classification. Objective three would result in a conceptual uncertainty framework providing a birds eye view of the solution. Finally, Objective four results in an uncertainty model, which would support decision-making, whilst prioritising key uncertainties.

1.5.2 Research Plan

The research presented in this thesis is based on a deductive approach (Ormerod, 2010). The existing theories stimulated identification of the research requirements, which then facilitated in synthesising the conceptual framework. The hypothesised conceptual uncertainty framework was operationalised and examined using an industrial scenario from the case study and satisfactory results were obtained. In a nutshell, the research methodology comprised of three phases moving deductively from conceptualisation, application and finally validation, which is discussed in next section.

The Table 1 presents the research plan mapping the research objectives, the adopted research methods and the chapter where they are presented in more detail.

Table 1: Research objectives and the methods adopted

Research objective	Method	Chapter
1) To define a framework to understand and quantify uncertainties in PSS delivered in business-to-business application.	***Literature study*** of uncertainty, PSS, availability contracts, uncertainty modelling ***Case study*** in availability contracts	3
2) To identify uncertainties affecting PSS delivery.	***Literature study*** of PSS, availability contracts and uncertainty research	4
3) To specify and develop a suitable uncertainty classification for uncertainties in PSS delivered in business-to-business application	***Literature study*** of uncertainty, PSS, availability contracts, BNs research ***Case study*** in availability contracts	5
4) To determine how uncertainties impact on the delivery of PSS in business-to-business application.	***Case study*** in availability contracts	6,7 & 8

1.5.2 Research Phases

The research process in this research can be described by three phases. The first phase is the conceptualisation phase, where a "mental image" of the PSS is constructed and provides an orderly framework within which the researcher can place all his perceptions related to the problem situation whilst deciding which aspects are relevant and which aspects are irrelevant for the structure of problem identified (Sagasti and Mitroff, 1971). Extensive literature review (see Chapter 2) enabled to conceptualise the construct for the uncertainty framework. This conceptual model represents a further degree of abstraction from reality and is capable of generating scientific models (Sagasti and Mitroff, 1971). Hence, conceptualisation phase provides a bird's eye view of the problem structure, which is transitioned to a lower level of abstraction in the next phase of the research process, by applying the conceptualised framework primarily using an industry case study as shown in Figure 6.

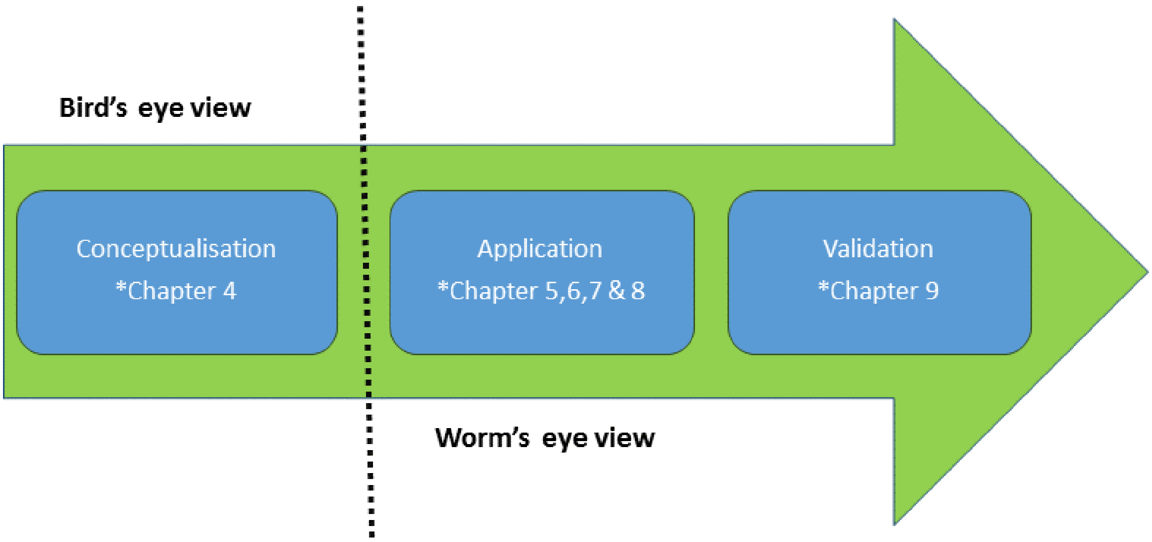


Figure 6: Research Phases

The application phase involves execution of the conceptual framework developed and defined in the conceptualisation phase. Different research methods, such as literature review etc. are used in this phase to specify concrete steps, which is then interpreted to a lower level of abstraction to form the worm's eye view. Case study is primarily used, where each concrete steps are realised. One of the conceptualisation was to identify uncertainties in PSS. It was mainly carried out by extensive literature review, which included four steps such as collation of literature relevant to PSS, identify variables, segregate variables into product, service and system list and finally identified variables relevant to the case study (see Chapter 4). The model structure was constituted based on insights from literature and case study (see Chapter 6), where procedure from literature mining was adapted. The final phase is the validation phase. Validation was carried out by comparison of simulation data with real industrial data, questionnaires, simulation and statistical analysis (Barth et.al. 2011). The model structure was validated using questionnaires, where industry contact personnel provided scoring on likert scale. Modelling results were validated statistically, using several features of the software employed. Satisfactory results were obtained, however there is potential for training the model with larger data sets (see Chapter 8).

1.5.3 Research Approach

The type of methodology depends upon the central research objective and questions (Miller and Crabtree, 1999; Denzin and Lincoln, 2000). It includes the various steps adopted by the researcher in studying the research problem and the rationale behind them (Kothari, 2009). The research approach adopted in this research is shown in Figure 7.

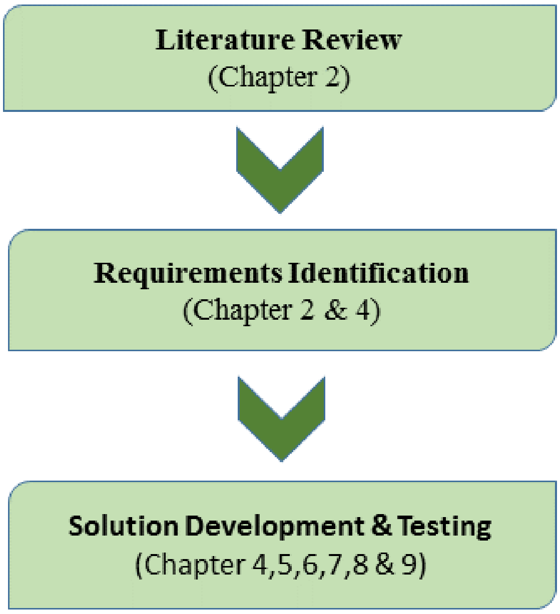


Figure 7: Research Approach Adopted

The required understanding of research areas relevant to the research aim was primarily developed through an extant literature review and was tested through a case study conducted in availability contracts, where the partnering industries work towards delivering availability of an avionics equipment. The various steps in the research approach adopted in this research is discussed below.

I) Literature Review

An extensive literature review is the foundation of successful research (Dhingra, 2011). The purposes of carrying out a literature review in this research are to: (1) determine the research gaps in the existing studies (2) understand the theoretical and conceptual foundation of the chosen research area (3) find the variables directly or indirectly impacting the research area (4) characterise the relationship between variables or sub-variables, where output from this process leads to the development of testable hypotheses (Dhingra, 2011). An appreciation of the variables, their definitions, how they can be manipulated and measured is of profound importance (Currier, 1979). Variables and uncertainty are used interchangeably (Swamidass and Newell, 1987), but a distinction between the two terms is acknowledged in this research. Definitions and the difference between the two terms is discussed in Chapter 4. Extensive literature review, primarily focussed on journal and conference publications, was carried out to explore different research areas such as PSS, availability contracts, uncertainty and uncertainty modelling techniques. It was found that the research areas covered were large independent areas with extensive work done. However, there was limited research found at the interface where all these research areas merge, as represented by the central shaded portion in Figure 8. And also research at the interfaces between research topics such as uncertainty, PSS and availability contracts was sparse.

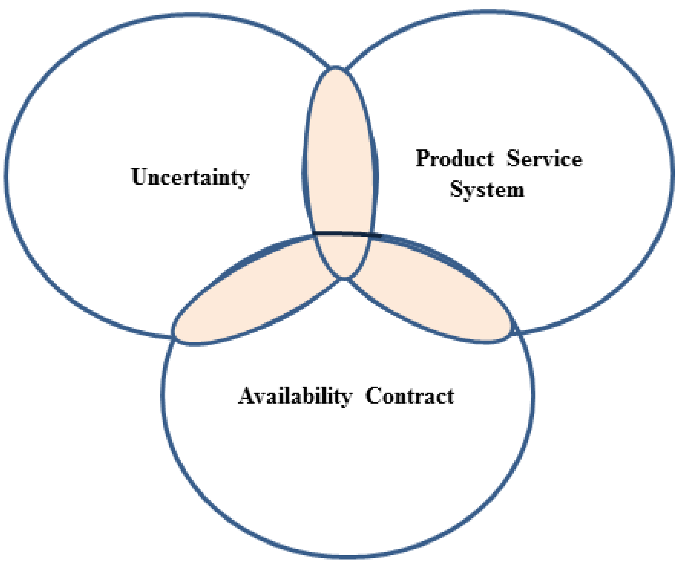


Figure 8: Primary Literature Review Areas

Reviewing this literature enabled in identification and analysis of the research gap, as discussed in Chapter 2. The main question in the literature review was on uncertainty challenges in PSS delivered in business-to-business applications. Literature related to uncertainty classifications was also found. In general, there are numerous uncertainty modelling techniques discussed in literature, such as possibility theory, evidence theory, interval theory, Monte Carlo Analysis, imprecise probabilities (Zio and Pedroni, 2013).

II) Requirements Identification

Literature review aided in articulating the requirements that need to be addressed in order to handle uncertainties. These requirements were synthesised to form a conceptual uncertainty framework, which is presented in Chapter 3, and is applied to a case study. Realisation of the requirements would improve the understanding and quantification of uncertainties in PSS delivered in business-to-business application. The requirements in essence would specify the key features required of an uncertainty modelling technique for PSS in business-to-business applications, need to utilise characteristics of uncertainty in a pragmatic manner and reasons the significance of knowing the individual uncertainties themselves. These requirements contributed in the development of the solution.

III) Solution Development and Testing

The solution is a conceptual uncertainty framework representing the bird's eye view, which is used to identify the detailed steps and tested by various choice of approaches informed by the requirements specified in the worm's eye view. Interaction with industry during steering meetings, working meetings and industry visits confirm the findings from literature. Case-study is a method for detailed contextual analysis of an event or conditions and their relationships, where multiple data collection techniques are used which enhances cross-validation and strengthen the results (Noor, 2008). Data collection techniques employed within the case study was mainly from semi-structured interviews, questionnaires, documents and database. Literature was also used to find uncertainties in PSS and procedures such as literature mining was adapted to unveil relationship between uncertainties. The various data collection methods employed and specific details such as interview questions are presented in the relevant chapters and appendices.

Semi-structure interviews were conducted for elicitation of probabilistic and dependency information about uncertainties, which is discussed in detail in Chapter 7. Semi-structured interviews provide flexibility (Easterby-Smith et.al. 2012) and it allows for face-to-face interaction, where the interviewer can provide clarifications to the respondents on any questions and avoid common biases such as availability, over-confidence etc. during probability elicitation (Renooij, 2001). The SRI protocol employed for eliciting prior knowledge prescribes face-to-face interaction (Spetzler and Stael Von Holstein, 1975 and Stael Von Holstein and Matheson, 1978) and semi-structured manner of questioning was most appropriate due to its flexibility. Five interviews were conducted spanning from an hour to two hours each. The interviewees were in job profiles ranging from director level to shop floor technician and they were all involved in activities affecting the delivery of MHDD availability to customer. The interviewees were forwarded with questionnaires and initial briefing material prior to the interviews. With respect to question format, interviewees in general feel uncomfortable with supplying probabilities directly and prefer other more graphical answering formats such as checkboxes or graphs (Cooke, 1991). To overcome this, an online probability elicitation tool called MATCH uncertainty elicitation tool (Morris et.al. 2014) was used, which provided a graphical interface with sliding bars to adjust values, fitted distribution for verifying etc. Questionnaires were used for validation of the model structure, which was forwarded to the three industry contact personnel of the CATA team. Likert scale, a psychometric scale commonly involved in research that employs questionnaires (Boone and Boone, 2012) is employed for validation. The format of the likert scale used included five-level, such as strongly disagree, disagree, neither agree nor disagree, agree and strongly agree. Questionnaires are easy to administer, convenient to the experts, inexpensive and avoids any interviewer variability (Bryman, 2012). Documentation included information about model checklist, repair process, key performance metrics and excerpts from the FRCAS (Failure Reporting, Analysis and Corrective Action System) database. These documentations were provided to the CATA team. Data was in excel format and available across a range of years ranging from as early as 2003 to mid of 2013.

1.6 Thesis layout

This thesis contains 9 chapters. The literature review in Chapter 2 provides the groundwork for this research by comprehending the existing research trends and research gaps. Based on this, the research objectives are formulated in order to achieve the aim defined. Chapter 3 presents the conceptual uncertainty framework. Chapter 4 discusses the variables in PSS. Chapter 5 relates to characterisation of uncertainties using a multi-layer uncertainty classification. Chapter 6, 7 and 8 presents structure of the Bayesian Network, elicitation of expert judgements to provide input to modelling and finally, evaluation and validation of Bayesian Network. Structure of the thesis is outlined in Figure 9. Chapter 9 outlines the key research findings and their novelty.

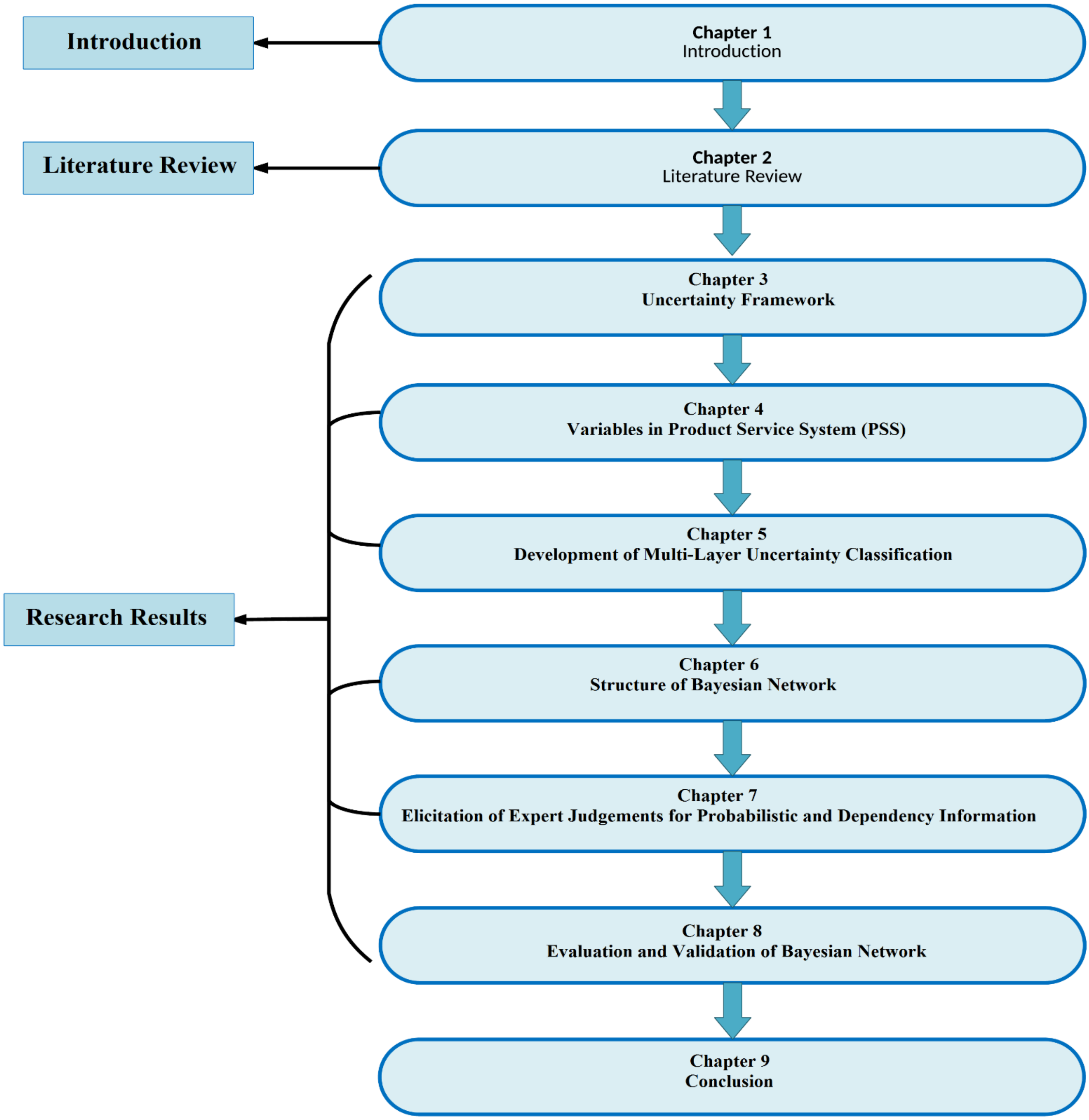


Figure 9: Thesis Structure

2 Literature Review

This chapter focuses on reviewing of literature relevant to the research area, with the purpose of identifying and analysing the research gap. It presents literature review in PSS (Section 2.1). Section 2.2 presents uncertainty and its various characteristics. Uncertainty modelling techniques implemented in research in the context of PSS is presented in Section 2.3. Bayesian Network as a potential technique to treat uncertainties is presented in Section 2.4. Finally in Section 2.5, research gap analysis is presented along with conclusion.

2.1 Product Service Systems

Research on PSS is extant and this increasing body of research indicates a growing interest in this topic by academia, business, and government. This chapter is structured as follows. Section 2.1 outlines various definitions of PSS and types of PSS. Followed by Section 2.1.1, which presents existing work on challenges faced in PSS as well as a synthesis of the key challenges identified after reviewing existing work. These challenges would play a key role in identifying the requirements of the uncertainty framework for purpose of understanding and quantifying uncertainty in PSS delivered in business-to-business application, which is presented in subsequent chapter. Section 2.1.2 addresses availability contracts as an exemplar for PSS in business-to-business application.

PSS has been defined by many researchers (Goedkoop et.al, 1999; Mont, 2004 and Manzini and Vezzoli, 2003). The first formal definition of product-service system (PSS) was given by Goedkoop et.al. (1999) as ‘a system of products, services, networks of “players” and supporting infrastructure that continuously strives to be competitive, satisfy customer needs and have a lower environmental impact than traditional business models’ (Baines et.al. 2007). Goedkoop et.al. (1999) also provides further clarity to their definition, by defining the key elements of PSS. Mont (2002) have defined PSS as a system of products, services, supporting networks and infrastructure that is designed to be: competitive, satisfy customer needs and have a lower environmental impact than traditional business models. Tukker (2004) have defined PSS as consisting of ‘tangible products and intangible services designed and combined so that they jointly are capable of fulfilling specific customer needs.

In this research, the definition presented by Goedkoop et.al. (1999) is adopted as it captures the meaning of primary elements of PSS and generic applicability. Hence, the definition of PSS adopted in this research is as follows:

- Product is a tangible commodity manufactured to be sold. It is a physical element which is influenced by gravitational force and has the ability to fulfil customer's needs.
- Service is an activity (work) done for others with an economic value and often done on a commercial basis.
- System is a collection of elements including their relations.

PSS can be offered through three types of innovative business models (Meier et.al. 2010). The three types of PSS business models include product-oriented, use-oriented and result-oriented business models. Product-oriented business model involves the typical sale of the product but accompanied with some additional services such as maintenance contracts, repair, re-use and recycling and may also include training and consulting for better operation of the product. In use-oriented business model, the product is the main component but the ownership of the product remains with the supplier. The product is available to customers by leasing, sharing, pooling etc. In result-oriented model, the main focus is on the desired outcome or result which the customers demand for and not the product. Here payment of the customer depends on the desired level of availability or capability provided by the OEM. It is the more sophisticated business model representing the popular features of PSS (Baines et.al, 2007). In addition to these types of PSS, Neely (2008) proposed integration-oriented PSS and service-oriented PSS. When services are added as firms move downstream and vertically integrating, it is called as integration-oriented PSS and when services are added to products by firms, by integrating the services into the product, it is called as service oriented PSS. The type of PSS discussed in this research is use-oriented, which is executed within the frame of availability contracts.

2.1.1 Challenges in Product Service System

Research on PSS is not new, however, the detailed practices and processes to deliver integrated products and services needs further exploration (Baines et.al. 2009a). PSS is an advancement of the concept of servitisation, as discussed in Chapter 1. Servitisation is a term coined by Vandermerewe and Rada (1989) and is now widely acknowledged as the process of creating value by adding services to products (Baines et.al. 2009 b). Some drivers for this is that, servitised manufacturers are in greater danger of bankruptcy and make lower return on investment in the long term (Neely et.al. 2011). Manufacturers are exposed to increased pressure, when offering PSS, quite simply because servitised manufacturer interacts closely with customers throughout the extended lifecycle at multiple contact points and are obliged to respond to increased demand signals, where the demands go beyond typical production operations like, target around cost, quality and delivery of products (Baines et.al. 2009a).

Baines et.al. (2009a) present five challenges that that a typical manufacturer experiences in supporting servitisation process model, related to language of services; value dimensions of integrated products and services; designing of products and services; integrated delivery systems and organisation transformation as a whole.

Sundin et.al. (2009) found challenges related to marketing of PSS, development of PSS, setting of cost price, usage of new technology and environmental issues by conducting workshops with large companies forming learning networks with the intention for continuous improvement of their work with developing and offering PSS. It was found that much of the challenges are related to changing different people's mindset whether it is within the company and/or with external companies and customers.

Parida et.al. (2013) conduct exploratory study of two case companies and found that a win-win collaboration between the PSS provider and the delivery network organisations, is not a natural outcome and could result in "win-lose or lose-win" situations. They also presented six prominent relational challenges that can negatively influence the likelihood of "win-win" collaboration among the organisations, which include managing relations over great spatial and cultural distances; to balance contributions and rewards from partners in the value chain securing long-term win-win relations; to handle a great variety of different partners referring to size, competence and ownership; to take life-cycle perspective into consideration and to revise the existing routines to augment internal communication within the organisations and to develop partner knowledge to enhance and communicate value in the network.

Martinez et.al. (2010) conducted qualitative research based on a single case study, where they addressed challenges faced by manufacturers adopting servitisation as a new strategy for achieving competitive advantage. They proposed five pillars, constituting the architecture of challenges in servitisation, which include embedded product-service culture, delivery of integrated offering, issues related to internal processes and capabilities, strategic alignment and the issue that arise because of this challenge are absence of internal cooperation, common language and alignment of mind sets that slows down transformation efforts and the final challenge is related to supplier relationships.

McMahon and Ball (2013) present challenges related to information technology and socio-technology. The former challenges included understanding of complexity and interlinked nature of engineering information, computing issues, lack of compatibility between software systems (between competing systems and between different generations of the same system), difficulties arising due to incorporation of proprietary features in software tools, differences in conceptual design of software tools, Inaccessibility of data created by different software tools after the software is retired or replaced, interoperability of data over multiple revisions of hardware, setting up and managing information archives and organisation of data for ease of finding it and generation of new knowledge from discovery of patterns in data. Socio-technical challenges include security, privacy and other user concerns and understanding how information systems can be embedded in organisational cultures and work practices.

After reviewing the literature on challenges encountered in PSS, some of the challenges which were recurring across the literature was related to integration of product and service elements as unified offering to the customer, consideration of lifecycle perspective of PSS, pricing of PSS when offered under contractual arrangements between the PSS provider and customer, issues related to collaboration among organisations involved in PSS offering and issues related to value and quantification of this value. The challenge of integration of product and service elements of PSS, highlights the system aspect of PSS. System perspective of PSS is a challenge that needs to be addresses especially in the context of uncertainty. Decision making in PSS challenge is usually addressed with respect to the pricing decision at the bidding phase of PSS (Kreye et.al. 2011a; Erkoyuncu et.al. 2011b). However, decision making in PSS delivery phase has received less attention. There is also sparse literature on uncertainty challenges in PSS, although some researchers do highlight the need for considering uncertainties in design and development of PSS (Sundin et.al. 2009). Four key challenges in PSS delivered in business-to-business application can be identified, which would highlight the significance of the impact of uncertainty. These challenges include scope of uncertainties, system perspective of PSS, PSS life cycle and decision making in PSS, as presented in Figure 10. A further discussion on these challenges is presented in the subsequent paragraphs, as they form important literature leading to identification and analysis of research gap discussed in Section 2.5.

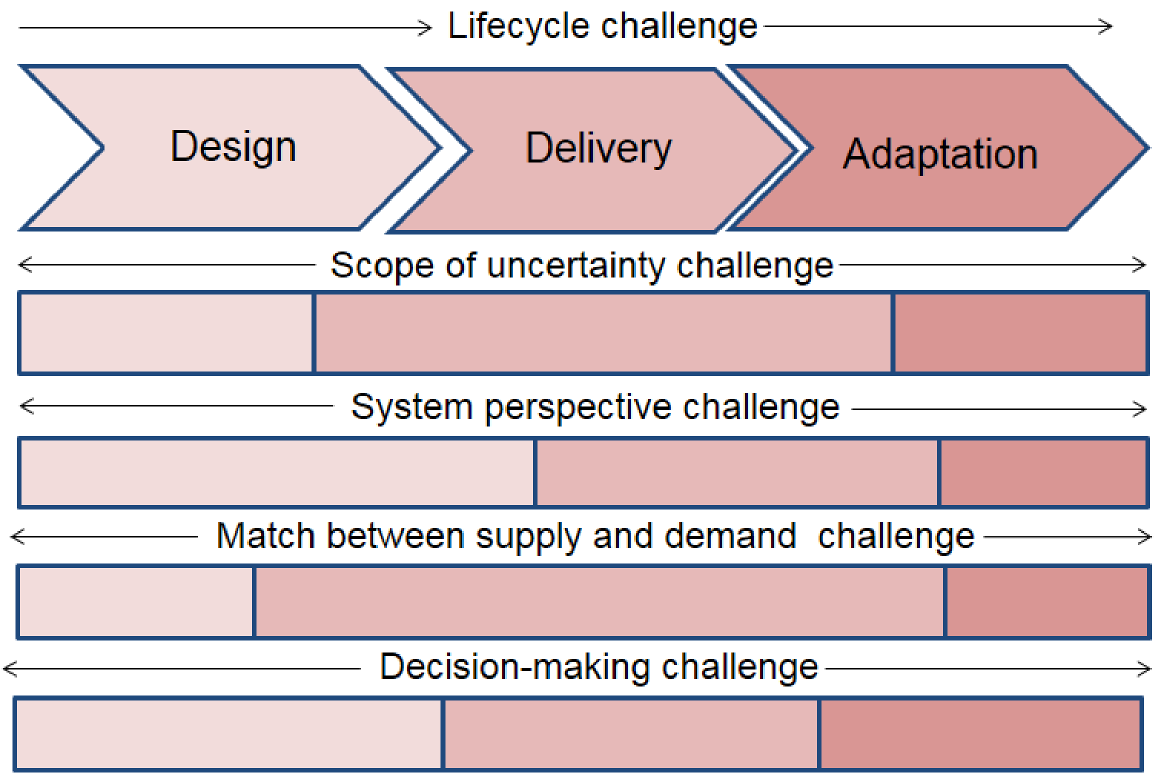


Figure 10: Challenges in PSS

Scope of Uncertainties

Servitisation places services in the lead role (Vandermerwe and Rada, 1989), and hence there is a need to understand the uncertainties arising due to this shift towards services. Service characteristics are intangibility, heterogeneity, inseparability and perishability (IHIP) (Ng et.al. 2008). These service characteristics have been widely acknowledged in research (Edgett and Parkinson, 1993; Zeithaml et.al. 1985, Lovelock, 1999). Organisations are confederated with widened scope for uncertainty and risk.

The uncertainties arising because of inseparability characteristic of service includes uncertainty in contracting at present time, it impacts the service value delivered to the consuming community and in turn influences the buying community at the contracting stage, uncertainty on the level of service value expectation and expected value of the future service may be discounted by the customer at the contracting stage (Ng et.al. 2008). Intangibility characteristic of services is a major source of performance ambiguity as it is difficult to develop output measures for services, to display or communicate them and the customer may not be owning anything tangible in the end (Edvardsson et.al. 2005). It also causes negative effect on organisation performance due to increasing reproduction of service processes in the market, which is developed in haphazard manner (Brentani, 1989). Heterogeneity can be in terms of service providers and service process or in terms of employee induced variation or variation among customer needs and expectations. Uncertainty in the form of service role ambiguity may exist as customer is a co-producer in service process. It also causes uncertainty due to difficulty in standardisation, direction guidelines for process and determinism in results. Perishability nature of services causes uncertainty related to task characteristics and task interdependencies aspect of capacity management. Inseparability of production and consumption causes uncertainty in quality assurance and quality control, as services cannot be provided in advance and checked before delivery. Servitisation process transits a traditional manufacturer to a service provider and this result in significantly more variables arising and an investigation into these variables impacts the success achieved in this transition (Bianchi et.al. 2009). Hence, the first step in kick-starting the process of understanding the uncertainties is to identify them. Cataloguing of uncertainties in PSS evolving from the servitisation process would aid in understanding the nature of uncertainties, inter-dependencies between these uncertainties and also highlights the need to prioritise key uncertainties. There has been some research focalised on enlisting uncertainties in PSS (Phumbua and Tjahjono, 2010; Visnjic and Looy, 2011; Dean 2004; Erkoyuncu et.al. 2011; Matzen and Andreasen, 2006 and Kuo and Wang; 2012). However, there is still a need for comprehensive enumeration of all the uncertainties in PSS considering each of its elements (uncertainties related to product, service and system) separately.

System Perspective

Mont (2004) state that for successful implementation of PSS, organisations need to adopt a system approach, which allows for improved system variables and conditions. System variables traditionally discussed are related to external demands and requirements (Mont, 2004), but PSS are inflicted by extraneous variables due to the integration of product and service offered as a single package, for example customer participation, equipment usage, retrograde time, operating environment etc. are the variables acting at the interface between product and service. The variables present at the interface between product and service play a critical role in PSS and needs to be dealt with, for successful design, development and delivery of PSS. Baines et.al. (2007) suggest that companies must move from ‘product thinking’ to ‘system thinking’, when designing PSS. The definition of uncertainty and PSS adopted in this research are from systems theory perspective, as discussed in Section 2.2.1.

Lifecycle approach

Designing of product and service by adopting a lifecycle approach is a key factor when developing PSS offerings (Datta and Roy, 2010). Design, delivery and adaptation are the three main phases of the lifecycle of PSS (Datta and Roy, 2010). When PSS delivered in business-to-business application are set in a contractual arrangement, which could range from 5 to 30 years, they are mostly impacted by varying customer demand with eventual variations in the requirements and processes over time and hence, a well thought-out adaptation phase would enhance the business to be more competitive and successful (Datta and Roy, 2010). In order to deal with these variations, planning ahead would be essential in PSS and hence forecasting is significant in PSS. Forecasts are the first step of the planning process in organisations and drive decision making concerning resources and equipment allocation (De Coster, 2011). Goh et.al. (2009) state that epistemic uncertainty which is due to future decisions and events may be assisted using forecasting methods and earlier these uncertainties are taken into consideration the more robust decisions are achievable. Unlike the traditional product forecasts, forecasting methods for PSS also needs to consider 'softer' management aspects of customer satisfaction of service operations (De Coster, 2011).

Match between supply and demand

Concept of match between supply and demand in service came as a breakthrough in 1976, when Sasser (1976) article "Match supply and demand in service industries" was published in Harvard Business Review. The characteristics of service such as its inability to be inventoried, the high degree of interaction between service provider and customer, non-portability of service and the intangibility nature of service output are factors which the service provider has to consider unlike in manufacturing (Sasser, 1976). For example, customers' participation in service creates uncertainty in process times, product's quality and facilities to accommodate customer needs. In order to capture this concept, a modelling method which can represents all uncertainties associated to supply and demand in the same model space is required.

Decision-making in PSS

Steven and Richter (2010) suggest it is neither possible nor sensible to make all decisions simultaneously but rather adopt a problem-driven decomposition would be essential, segregating decisions to top level, which is the development phase of PSS and base level, which refers to the operating phase of PSS. Hence, appropriate tools and techniques that would support decision-making in PSS would lessen the burden associated to planning in PSS.

Changes in traditional structures is a demand to be met by organisations, both manufacturing and service organisations endeavouring towards offering PSS and this calls for close co-operation with customers with increased interaction and hence, structure of decision-making inclines to be more decentralised (Mont, 2002).

Planning of resources during delivery of PSS subject to various uncertainties is of utmost importance in delivery of PSS, where there is lack of decision support in determining robust capacity planning strategies (Lagemann and Meier, 2014). They highlight uncertainties unique to resource planning in PSS, which differ from production planning and scheduling, which include external uncertainties due to integration of external factors such as customer personnel, machines or other resources; internal uncertainty due to collaboration of different delivery partners, sudden loss of capacity or due to duration of delivery processes, which are less standardised than manufacturing processes; uncertainty due to high levels of time criticality involved in service delivery processes, which requires careful consideration in travel planning and tool and spare part management because transfer of risk to the service provider can have serious financial consequences for any equipment downtime or bottle necks in capacity supply and finally, uncertainty due to perishability of PSS service delivery processes due to which they cannot be stocked like products to meet demand peaks.

2.1.2 Availability Contracts

In availability contracts, novelty lies in the fact that customer pays for use of the product and service that is provided and the OEM retains product ownership. Availability contracts are discussed and sometimes even used synonymously under an umbrella of terms such as performance based logistics (PBL) or outcome based contracts (Nowicki et.al. 2008; Ng et.al. 2009). The U.S. Department of Defence (DoD) is rapidly implementing of PBL strategy and this is evident from the large amount spent on sustainment and DoD has engaged in 215 PBL programs (Nowicki et.al, 2010). They have also had a target set to achieve a minimum of 50% of acquisitions to be performance-based by end of 2005 in the three defence services (Army, Navy and Air Force) (Rievley, 2001). A similar trend was seen in U.K. defence sector, which is transitioning toward contracting on availability and capability for such weapon systems as Tornado and Harrier aircrafts, Apache, Merlin and Chinook helicopters, Type 45 destroyers and Astute class submarines are among many others (Ripley, 2005). There is substantial reduction of costs due to higher efficiency in support services and enhanced availability is evident from cases like this, Royal Air Force in the U.K. is expected to reduce costs by 12% in the outsourced maintenance of its fleet of E-3D Sentry Airborne Warning Control System (AWACS) aircraft (Sols et.al. 2007). PBL in commercial sectors has emerged as a strategy for improving performance and lowering the cost to sustain complex systems (e.g., passenger aircraft, and high-speed rail) during the post-production phase of their life-cycle (Randall et.al, 2010). Other factors which has made availability contracting popular in the last decade is decline in manufacturing profitability, due to arising of alternative low cost products from developing countries (Martinez et.al, 2010).

Availability contracting to a large extent has augmented the level of uncertainty that the manufacturer faces (Roy and Erkoyuncu, 2011) and projects executed under the frame of availability contracts attract additional uncertainties, especially at the service delivery stage (Roy and Erkoyuncu, 2011). Research about uncertainties in availability contracts especially in cost estimation has received attention recently (Erkyouncu et.al. 2011a, Erkyouncu et.al. 2011b, Erkoyuncu et.al. 2014; Roy and Erkoyuncu, 2011). Ng and Yip (2009) found that service delivery in availability contracts is innovative and pre-emptive and could reduce the overall costs because of the reduction in spares usage etc. and at the same time increases uncertainty in forecasting cost. However there are challenges arising at a strategic or higher level impacting the way uncertainties are dealt with. One such challenge faced in availability contracting is the alignment between stakeholder goals. Alignment of different stakeholder goals through incentives to meet the customer-oriented key performance indicators is a key aspect (Kapletia and Probert, 2010). Supply chain optimisation is determined by how a set of performance metrics is achieved (Beamon, 1998). There is a need to minimise loss generated with conflicting goals in supply chains by matching the performance metric of individual supply chain with those of the entire supply chain (Lee and Whang, 1993).

2.2 Uncertainty and its Characteristics

Uncertainty is ubiquitous. In order to understand uncertainties, we need to understand all the fundamental aspects of uncertainty such as its definition and its various characteristics. Section 2.2.1 attempts to unfold and review the definitions of uncertainty existing in literature. When uncertainty is spoken of, risk is a very close topic which nearly overlaps or may be even merges with uncertainty. Hence relationship between uncertainty and risk is also looked into in Section 2.2.2, to understand the difference that exists and clarify any ambiguities. Section 2.2.3 presents all the existing uncertainty classifications, discussing the various categories and purpose of the uncertainty classification.

2.2.1 Uncertainty

Uncertainty has been defined in various disciplines like operations research, economics, finance, engineering, within different fields of decision support like policy analysis, integrated assessment, environmental and human risk assessment, environmental impact assessment, engineering risk analysis, cost-benefit analysis, in social sciences which further has many sub-areas like management, system analysis and in the vast area of engineering which includes areas such as control and dynamical systems, civil, structural and environmental areas, management science, computational methods and simulation, mechanical, aerospace, design and metrology (Walker et.al, 2003; Thunnissen et.al 2003).

A clear definition is the starting point for all research (Baines et.al, 2007). However, there has been no consensus on a standard definition of uncertainty. Most of the definitions encountered in the literature review were generic and adopted a lexical definition to proceed with the research. Walker et.al. (2003) defined uncertainty as any deviation from the unachievable ideal of completely deterministic knowledge of the relevant system. Kreye (2011) adopts definition of uncertainty as a potential deficiency in any phase or activity of the process which can be characterised as not definite, not known or not reliable (Soanes, 2005). The definition adopted by Thunnissen (2003) for uncertainty is described as "liability to chance or accident", "doubtfulness or vagueness", "want of assurance or confidence; hesitation, irresolution", and "something not definitely known or knowable" (Murray, 1961). In reference to design of engineered products and services, Weck et.al. (2007) refers to the term uncertainty as an amorphous concept that is used to express both the probability that certain assumptions made during design are incorrect as well as the presence of entirely unknown facts that might have a bearing on the future state of a product or system and its success in the marketplace. In the context of modelling, uncertainty has been defined as a potential deficiency in any phase of activity of the modelling process that is due to lack of knowledge which causes the model-based predictions to differ from reality (AIAA 1998). In engineering analysis and design, uncertainty is commonly defined as knowledge incompleteness due to inherent deficiencies in acquired knowledge (Ayyub and Klir, 2006).

Some definitions are generic (Walker et.al. 2003) and some are tailored to the context of the purpose they are investigated in (Weck et.al. 2007). It can be observed that most researchers who have proposed uncertainty classifications have adopted a definition of uncertainty that reflect generic aspects of uncertainty such as lack of knowledge, unknown etc. They emphasise on the knowledge aspect, which is core to most definitions adopted. Uncertainty has been often related to something residing in the mind of a decision maker or something associated to a measurement. This distinction of objective and perceived uncertainty is discussed by researchers and uncertainty associated to the characteristic of environment which can be measured objectively is the former, while uncertainty depending on the process by which individuals organise and evaluate stimuli from the environment is the latter (Meijer et.al. 2006). In this research, the definition of uncertainty adopted, addresses both objective and subjective notion of uncertainty. The definition takes a knowledge perspective, which has both objective and subjective interpretations. Hence, *uncertainty is defined as any deviation from the unachievable ideal of completely deterministic knowledge of the relevant system (Walker et.al. 2003),* in this research.

2.2.2 Risk and Uncertainty

In 1901, definitions of uncertainty and risk was given by economist Willet (1901) in his thesis where he defined risk as the ‘‘objectified uncertainty regarding the occurrence of an undesirable event’’ and subjective uncertainty ‘‘resulting from the imperfection of man's knowledge’’ as uncertainty. Later in 1921, Frank Knight defined quantifiable uncertainty as ‘risk’ which means probabilities can be assigned and non-quantifiable uncertainty as ‘uncertainty’ which means assignment of probability is not possible (Knight, 1921). Thunnissen (2003) makes a distinction between risk and uncertainty in accordance with Frank knights definitions according to which probabilities can be assigned to risk while uncertainty cannot have probability assignments.

The common distinction found between uncertainty and risk is that the former can be both a threat such as the probability of failure of material or an opportunity for example as innovation and progress (Ullman, 2008) and latter always associated with a potential loss. Along the same lines, Garvey (2000) defines risk as the chance of loss or injury. He emphasises that uncertainty is analysed for the purpose of measuring risk. Samson et.al (2009) proposed a modelling approach attempting to model uncertainty as a non-quantifiable interval, which eventually aids in modelling risk as quantifiable probability distributions. Samson et.al (2009) define risk in terms of uncertainty. They define risk as the probability of an unsatisfactory system response quantified by a random function of the uncertainty. They suggest that uncertainty and risk are usually related; uncertainty gives rise to risk. The various possible relationships between risk and uncertainty discussed in Samson et.al. (2008) is shown in Figure 11.

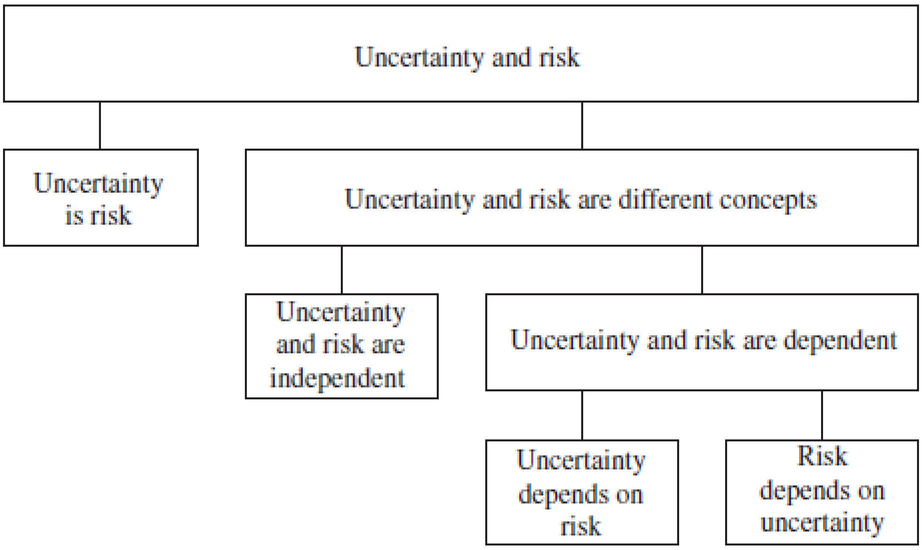


Figure 11: Relationship between uncertainty and risk (Samson et.al. 2009)

Ward and Chapman (2003) made a distinction between risk and uncertainty in project management context. According to them project risk management has a threat and event based perspective, whereas project uncertainty management takes both threat and opportunities into account, therefore widening the scope of considering uncertainties in project life cycle. Reiterating a similar concept, Kaplan and Garrick (1981) present the relation between risk and uncertainty in a very concise manner in equation format as shown below,

Risk = uncertainty + damage **(**Kaplan and Garrick, 1981)

From reviewing the literature related to difference between risk and uncertainty, the following conclusions are drawn for this research. Uncertainty and risk are two different concepts. Uncertainty comprises of loss or any potential opportunities identified. This widens the scope of uncertainty. Risk refers to pure loss or damage and no opportunity for an 'opportunity' arising. Uncertainty evolves into risk and therefore, an uncertainty could be a potential risk with time. Hence, research conducted further in this thesis adheres to this difference. Any research related to risk perceived as significant is considered in this research, under the view that uncertainty gives rise to risk.

2.2.3 Uncertainty Classifications

Various classifications of uncertainty have emerged in various fields, this can be attributed to the fact that various fields from economics to engineering have an emphasis on one aspect of uncertainty which most impacts that particular field and the classifications are proposed to address that problem area (Thunnissen, 2003). Hence, classifications of uncertainty have been developed for many purposes and are context or problem dependent (Walker et.al, 2003; Thunnissen et.al 2003; Refsgard et.al, 2007).

A five layer uncertainty classification was presented by Kreye et.al (2011b) for the purpose of identification of part of the design process which is most influenced by uncertainty and the classification included nature, cause, level, manifestation and expression, where manifestation characteristic of uncertainty was further expanded into context uncertainty, data uncertainty, model uncertainty and phenomenological uncertainty. The five layer uncertainty classification is an extension of Walker et.al (2003) three dimensions of uncertainty of nature, level and location. The term location has been changed to manifestation, to reflect that uncertainty resides at point in the design process rather than a physical location. Thunnissen (2003) presents a classification of uncertainties for the design and development of complex systems, which includes ambiguity, epistemic, aleatory, and interaction as main types of uncertainty, as shown in Figure 12. Epistemic uncertainty is further subdivided into model form, phenomenological, and behavioural uncertainty.

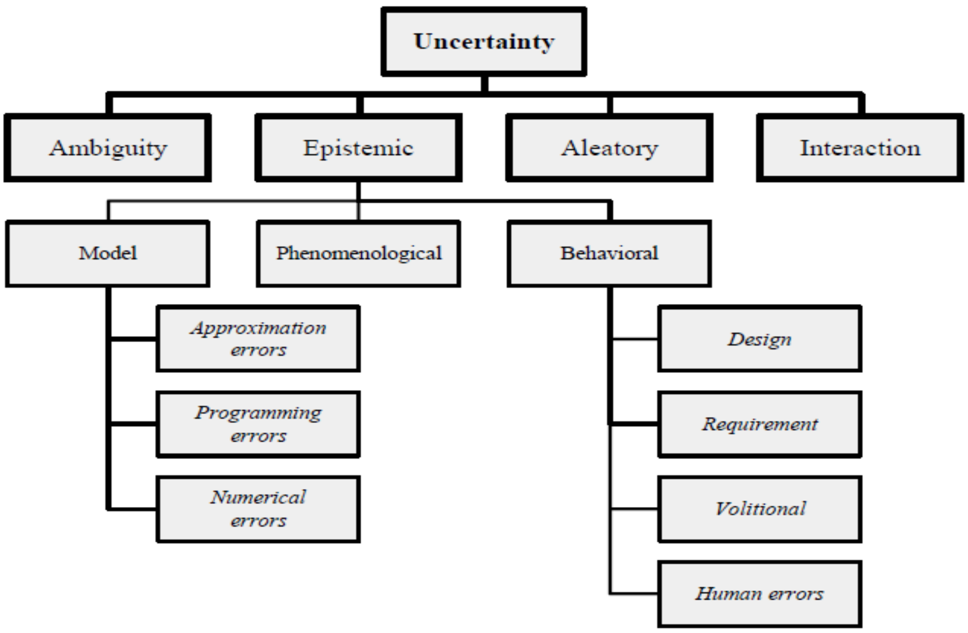


Figure 12: Uncertainty Classification for the Design and Development of Complex Systems (Thunnissen, 2003)

Walker et.al (2003) propose three dimensions of uncertainty, which include location, level and nature of uncertainty in the context of policy decision making and proposed an uncertainty matrix as a heuristic tool to handle the various dimensions of uncertainty. This has been used by other researchers (Refsgard et.al, 2007 and Kreye et.al, 2011b) to derive their own typology of uncertainties. Ward and Chapman (2003) identify five areas of uncertainty in project management which are, variability associated with estimates of project parameters; basis of estimates of project parameters; design and logistics; objectives and priorities and finally relationships between project parties. Weck et.al. (2007) proposed a classification of uncertainty from product design or system design perspective. They mainly classified uncertainty into endogenous or internal uncertainty, which was further classified depending on the context into product and corporate context. Second category was exogenous uncertainty which further branched into use context, markets, political and cultural context. Erkoyuncu et.al. (2011a) propose a classification of uncertainties with the purpose for better assessment of uncertainty, which in turn would enhance performance improvements of support delivery and cost estimation of PSS delivered in business-to-business application. Uncertainty is categorised into commercial, affordability, performance, training, operation and engineering areas and referred to as CAPTOE (Erkoyuncu et.al. 2011b). Erkoyuncu et.al. (2011a) also enlisted a number of uncertainties under each category of uncertainty. Although the list is comprehensive, it requires further refinement in terms of uniformity in granularity. Some of the uncertainties described were highly abstract such as supply chain logistics, whilst others were more specific like the hardware failure rate. The approaches to development of uncertainty classifications discussed above, further clarifies that typologies of uncertainty are more practical and utilisable when it addresses some specific research area, than be in a blind pursuit for uncertainty classifications which are generic in nature and not of much use, in practical sense.

2.3 Uncertainty Modelling in PSS

Uncertainty modelling within PSS in business-to-business applications that has received much attention is in the area of cost estimation and price bids for service contracts in early bidding stage (Erkoyuncu et.al. 2011a; Erkoyuncu et.al. 2011b; Roy and Erkoyuncu 2011; Kreye et.al.

2011a, Kreye et.al. 2012). Research addressing uncertainty modelling as an explicit area of investigation in PSS is limited. In existing research, Agent-based modelling (ABM), Analytical Hierarchy Process (AHP) and fuzzy-based modelling approaches have been used to model uncertainty in PSS delivered in business-to-business application (Roy and Erkoyuncu, 2011; Lagemann and Meier, 2014; Erkoyuncu et.al. 2011a; Erkoyuncu et.al. 2014; Wang and Durugbo, 2013; Janz, 2006). These modelling approaches are used to address different issues surrounding uncertainty, for example, prioritisation of uncertainties or the dynamism of uncertainties at play, and for different purposes such as cost estimation, evaluation of different PSS propositions for the organisations to adopt or evaluation of supplier capabilities for collaborating to adopt PSS. The author reviews these approaches in this section, to understand their pros and cons and compare their capabilities to address the purpose. Roy and Erkoyuncu (2011) segregate uncertainty modelling approaches for the purpose of cost estimation in PSS, into techniques aiming to handle data issues and techniques aiming to handle the stochastic nature of services. The former category consists of possibility theory, fuzzy set theory, neural networks and evidence theory. In the latter category, Monte Carlo simulation and stochastic models are included. The modelling techniques discussed in this section are the most recent uncertainty modelling techniques employed in the context of PSS (business-to-business application), where some are simulation models and some are analytical modelling approaches. Section 2.3.1 discusses Agent-based modelling (ABM). Followed by Section 2.3.2 which presents Analytical Hierarchy Process (AHP). Section 2.3.3 addresses Fuzzy modelling approaches and Section 2.3.4 presents Bayesian Network (BN). Section 2.3.5 concludes by comparing key characteristics of the various modelling techniques and suggests BN as a potential choice for modelling uncertainties in PSS.

2.3.1 Agent-Based Modelling (ABM)

ABM provides solution in the form of explanatory rather than predictive purposes, hence suitable for the bidding phase of PSS, where issues arising due to data are influential (Roy and Erkoyuncu, 2011). ABM facilitates more detailed analysis due to its enhanced computational power and its ability to handle increased amount of data at lower levels of granularity (Roy and Erkoyuncu, 2011).

Lagemann and Meier (2014) use an agent-based modelling to provide decision support for robust capacity planning for PSS in business-to-business application to enable service managers to test and evaluate the effect of costly capacity management options before implementing them in the service organisation. They adopt ABM using AnyLogic University 6.9.0, where machine agents and field service engineer (FSE) agents are present within the physical layout of the service organisation and are co-ordinated by the PSS delivery requests and assignments and their assignment to specific delivery process is based on their skills, geographical location and the urgency and criticality of delivery processes. Each machine is represented by an agent similar to the FSE's. Key performance indicators (KPI) are used to evaluate the system based on the difference between actual performance and target KPI. They claim that the ABM compared to analytical models can handle uncertainties and dynamics in the form of stochastic probability distributions and state dependent behaviour of agents. Unlike the analytical approaches, ABM provides a test environment for the evaluation of different capacity management options. The limitations as discussed by Lagemann and Meier (2014) relates to the validation of the simulation results which depends on the quality of simulation model and the available data. Due to this, there could be omission of important factors influencing the real service organisation. Some assumptions about the agent behaviour may not be applicable in reality. ABM only reveals the consequences of different capacity management options and would not be able to define suitable capacity management strategies. Hence, the planning task highly depends on the insights, creativity and understanding of the service manager who is working with the decision support tool.

Erkoyuncu et.al. (2011a) propose a framework to estimate costs for PSS in business-to-business application using two modelling approaches to address uncertainty. Firstly, AHP is employed to increase understanding of the influence of different uncertainties and cost estimation capabilities, hence bringing in rigour to assessing the impact of uncertainty on cost. And, subsequently employed ABM to represent the dynamism in service cost estimates. Hence, the cost estimation process uses two uncertainty modelling approaches feeding input to each other, although they address different aspects of uncertainty. One for prioritising the key cost drivers and the other for capturing the dynamism of uncertainties. The assessed uncertainties are coupled to specific cost drivers, then an uncertainty score for each cost driver is calculated using AHP and NUSAP matrix. This is used to specify suitable ranges for cost drivers. They present a simple high level model showcasing the various uncertainty sharing schemes between supplier supplying spares, supplier supplying resources such as agents and industry using three scenarios, which include uncertainty with industry, uncertainty with supplier and in the third scenario, industry and supplier share uncertainty. ABM of the three scenarios lead to the conclusion that transfer of risk to the industry resulted in the lowest whole life cycle cost and hence, it would be better for the customer to pass on all the risks to industry. Although, the uncertainty arising due to the dynamism of service delivery was captured by ABM, the scenario analysis was not in depth and not many possibilities were examined to gain deeper understanding of the various uncertainty impacts.

Roy and Erkoyuncu (2011) propose three conceptual architectures within the context of service cost estimation for PSS delivered in business-to-business application, which is implemented using ABM. Organisational perspective to capture the interaction across the supply chain, equipment perspective for the evolution of material or part requirements of the equipment and human perspective capturing the role of human in service provision are the three risk sharing scenarios respectively, described in the paper. The agents are defined as real-life organisations, equipment and humans in the three scenarios respectively, characterised with varying degrees of autonomy (execution ability and self-control) and characteristics based on policies, behaviours, states and constraints.

2.3.2 Analytical Hierarchy Process (AHP)

The Analytic Hierarchy Process (AHP) is a multi-criteria decision-making approach and was introduced by Saaty (1977). Erkoyuncu et.al. (2011a) apply AHP to enable users rank the importance of cost drivers that contributes to the assumed initial total cost using AHP and hence, the contribution of each cost driver is calculated. It was discovered that the most important cost drivers are transport cost and failure cost, based on the uncertainty score that was derived through AHP and NUSAP (Numeral Unit Spread Assessment Pedigree) matrix. NUSAP matrix enabled to translate the qualitative information elicited from experts into quantitative results, which enabled to classify uncertainties into high, medium and low level of uncertainties for services. Subsequently, AHP was employed to link the assessed uncertainties to specific cost drivers, which in turn enables in calculating an uncertainty score for each cost driver and range values for each cost driver are defined using the Association of Advancement of Cost Engineering (AACE) guidelines. The outcome from the AHP process is fed into the ABM.

Erkoyuncu et.al. (2014) propose a very similar methodology to Erkoyuncu et.al. (2011a) where they employ AHP and NUSAP matrix, as structured approaches to assess the influence of uncertainty on cost by means of prioritisation using AHP to identify the key sources of uncertainty. However, Erkoyuncu et.al. (2014) have introduced an additional step of calculating uncertainty score as a product of uncertainty level and uncertainty weight. Uncertainty prioritisation has both quantitative information and qualitative information elicited from experts, facilitating in identifying key uncertainties. Erkoyuncu et.al. (2014) claim that this approach, avoids the pitfalls of subjectivity involved in uncertainty prioritisation by implementing a quantitative scale to represent the experts subjective opinion. However, both modelling approaches still heavily rely on expert opinion and the improvement to uncertainty prioritisation brought about by the quantitative scale needs further investigation and validation.

2.3.3 Fuzzy-Based Modelling

Wang and Durugbo (2013) propose fuzzy-based techniques for evaluating and providing decision support to deal with uncertainties arising while moving towards provision of PSS in business-to-business application for an organisation which is involved in typical product-focused business. They employ fuzzy Delphi, fuzzy Analytical Hierarchy Process (fuzzy AHP) and fuzzy Technique for Order of Preference by Similarity to Ideal Solution (fuzzy TOPSIS) in their paper. They evaluate eight value propositions for PSS, which include product related services, advice and consultancy, product lease, product renting/sharing, product pooling, activity management/outsourcing, pay per service unit, and functional result to provide customers by prioritising uncertainties related to each value proposition. They outlines 82 uncertainties related to management, product and operations within literature. Durugbo and Wang (2013) propose a framework to prioritise sources of network uncertainty in PSS with a focus on collaborative readiness and industrial product service readiness. They use fuzzy extent analysis to determine the priority weights for uncertainties. The work presented in Durugbo and Wang (2013) and Wang and Durugbo (2013) are highly inter-related, where they are distinct in terms of their focus and difference in the analytical fuzzy methods implemented. Former focuses on evaluating network uncertainties to support the choice of value propositions for PSS in business-to-business application. Whereas the latter focuses on evaluating readiness of partnering firms to enter into collaborations for PSS. It could be noticed that uncertainty measurement items enlisted have both qualitative measures like complexity of critical material, complexity of procurement technology for critical material etc. and highly quantitative one's like number of sales channels, number of critical material suppliers etc. It may a pose problem for experts to compare uncertainties with extremely contrasting nature of quantitativeness and qualitativeness.

2.3.4 Bayesian Network Modelling

Janz (2006) adopt BNs to forecast Lifecycle Cost (LCC) of PSS due to the modelling methods ability to combine expert knowledge and collected lifetime data and also pointed that modelling using BN enables the plausibility of a given statement to be updated in the light of new information which in turn enhances accuracy of cost estimation. On a general basis, uncertainty forecasting could be to support various issues of concern related to PSS such as cost estimation, design and development decisions in the early phases of PSS, environmental impact of PSS or recycle/disposal decisions. Forecasts in PSS could also address whether or not existing contracts will be renewed, product sales forecasts or scope for bespoke/consultancy work forecasts (De Coster, 2011). Unlike the traditional product forecasts, forecasting methods for PSS also needs to consider 'softer' management aspects of customer satisfaction of service operations (De Coster, 2011).

2.3.5 Conclusion

This section has presented uncertainty modelling techniques used within the research area of PSS delivered in business-to-business application. ABM is time driven capable of capturing dynamic results distributed in time and space. However, the current implementation of ABM has not revealed detailed analysis of different PSS scenarios modelled. The current work done in ABM implemented to PSS addresses high level ideas of abstract nature for different scenarios within PSS. Prioritisation of uncertainties is key issue to be dealt in PSS because of the enormous scope of various sources of uncertainty. There has not been any research reported on conducting sensitivity analysis using ABM. AHP has been primarily used for prioritisation of uncertainties by reducing subjectivity involved in uncertainty prioritisation using a quantitative scale to represent the expert's subjective opinion. The effectiveness and improvement in the assessment of uncertainties due to the inclusion of quantitative scale and also the quality of the anchors used in the quantitative scale are issues to be addressed. Fuzzy-based modelling techniques can handle imprecise criteria well, however require complex computations. Fuzzy AHP makes pair wise comparisons and hence it is limited in use, when many complex interdependencies exist. BNs enable reasoning under uncertainty and combine the advantages of an intuitive visual representation with a sound mathematical basis in Bayesian probability. With BNs it is possible to articulate expert beliefs about the dependencies between different uncertain variables and to propagate consistently the impact of evidence on the probabilities of uncertain outcomes. BNs present a convenient high level language for explicit representation of dependencies or independencies between variables that lack numeric or functional details. Hence, BN is a suitable modelling technique to treat uncertainty. A table assessing modelling capabilities of the above mentioned modelling techniques is presented in the Table 2.

Table 2: Uncertainty Modelling Techniques

Modelling capabilities	ABM	AHP	Fuzzy	BN
Representation of complex interdependencies between variables (system representation)	yes	no	no	yes
Type of result (explanatory, prediction)	Explanatory	Explanatory	Explanatory	Predictive/Explanatory
Ease of updating results based on new information	yes	no	no	yes

2.4 Bayesian Network

Further to comparing various uncertainty modelling techniques applied to PSS, Bayesian Networks have been recognised as powerful tools for representing and analysing problems involving uncertainty. This Section presents different aspects of developing BNs, which needs thorough investigation in order to implement them. Section 2.4.1 presents the different methods for deriving the structure of BNs, which encompasses various methods from learning from expert knowledge to learning from literature available widely. Section 2.4.2 discusses different sources of probabilistic information and the methods for deriving prior probability distribution predominantly from expert knowledge. Finally Section 2.4.3 presents methods for elicitation of conditional probability distribution from expert knowledge.

2.4.1 Structure of Bayesian Networks

Building BNs is considered difficult and time-consuming work (Xuan et.al. 2007). The two significant obstacles in building BNs are, firstly determination of structure of BN and secondly, elicitation of Conditional Probability Tables (CPT) (Neil et.al.2000). Structure of BNs relates to having a sensible model of the types of reasoning being applied in the problem area and the latter pertains to probabilities derived from literature, data, expert elicitation or any combinations of these (Park and Cho, 2012). After reviewing the literature, it was found that BN structure can be derived in the following different ways.

i) From expert knowledge

ii) From data

iii) Using data and expert knowledge

iv) Using literature and data

v) From literature data

These approaches to building BNs are described in Appendix A. It was found from the review that a combination of literature and expert knowledge has not been explored to derive structure of BNs. This is a potential gap that needs to be addressed.

2.4.2 Elicitation of prior probabilities

Bayesian networks consist of a qualitative and quantitative part (Renooij, 2001). The qualitative part includes the variables and arcs which form the Directed Acyclic Graph (DAG). The quantitative part is the conditional probability tables which are populated with probabilistic information. In BNs, the quantitative part is completely specified by defining, for each variable with parents a Conditional Probability Table (CPT) and variables having no parents are specified by marginal prior probabilities (Bobbio et.al. 2001). This section discusses different sources of probabilistic information to acquire prior probabilities and focusses on methods for eliciting judgements from domain experts to obtain prior probabilities to quantify the BNs.

Probability elicitation, probability encoding and knowledge engineering are a few terms used when probabilities are extracted from domain experts (Spetzler and Holstein, 1975; Pradhan, 1994 and Renooij, 2001). Both numbers and words are used by humans to express uncertainty. Witteman and Renooij (2003) evaluate their probability elicitation approaches using a scale mapping verbal anchors and numerical anchors and found that a combinational use of the two resulted in accurate probability assessments and was easier for less numerate. Winkler (1967) proposed methods for eliciting probability distribution and classified them into direct and indirect methods (Winkler, 1967). Equivalent prior sample (EPS) and hypothetical future sample (HFS) methods are referred to as indirect methods because the distribution that is eventually used is not clear to the expert at the time of elicitation. Cumulative distribution function (CDF) method also known as variable interval method and the probability density function (PDF) method are the direct methods, where the distribution unveils to the expert as the elicitation proceeds.

To address situations where statistical information is not available or available information may not be directly usable in the network, for example in situations where variables are not numeric or domain expert is hesitant to provide probability estimates, Druzdzel and Van der Gaag (1995) propose a non-invasive method, which accommodates all the quantitative and qualitative information available from the expert by expressing it in a canonical form which has (in) equalities on hyperspace of possible joint probability distributions to derive second-order probability distributions over the desired probabilities. Hence, they attempt to identify probability distribution for a single variable over joint probability distribution hyperspace over all the variables by utilising all the qualitative and quantitative information elicited from the expert. Hansson and Sjökvist (2013) studied different methods for eliciting single probability as well as full Conditional Probability Tables (CPTs), where they found probability scale and likelihood methods showed best results. Probability scale was found to be easy and straightforward method for the expert to use, whereas likelihood method is suitable when the expert is not comfortable at expressing their beliefs as probabilities. They also suggest that coarse estimates of probabilities are adequate as a first stint for BNs because sensitivity analysis when carried out after an initial assignment of rough probabilities will unveil which node probabilities have a weighty impact on the networks output. These probabilities need a more accurate assessment and may also result in modification to network structure, when adding evidence to observable nodes influence on the network is recognised. There are two approaches to elicit probability distributions from experts, one involves asking questions on proportions, where values are elicited at different probabilities decided by the facilitator and on the other hand, facilitator specifies the values, at which probabilities are requested (O'Hagan et.al.2006).

Elicitation of Probabilities

Direct method for probability elicitation is where experts express their belief directly and include methods such as probability scale, whereas indirect method for example gamble-like methods, probability wheels is when expert makes a decision in a different situation, which implies his or her belief towards an estimate of interest, (Rennoij, 2001). However, these methods are usually not used for deriving probability distributions, as the elicitation may get exhaustive. However, Xuan et.al. (2007) have used probability scale has been used in the elicitation of CPTs (Xuan et.al. 2007), because of their ability for fast elicitation of a large number of probabilities for BN (Van der Gaag et al. 1999). Typically elicitation of probability distribution entails eliciting a (relatively small) number of summaries from experts and fitting a suitable probability distribution that conforms to the elicited judgements (Devilee and Knol, 2012). The most widely used assessments for probability distributions are central measure (a mean, median or mode) and the assessment of quantiles (O'Hagan et.al. 2006; Devilee and Knol, 2012). For the elicitation problem to be manageable, structure is imposed on the probability distribution used to represent expert's opinion for the elicitation problem, under the assumption that some specified parametric distribution fits the probability distribution summaries the expert specifies (Devilee and Knol, 2012). Hence the elicitation problem reduces to estimating the parameters of the probability distribution (Devilee and Knol, 2012).

Elicitation of Proportions

When the quantiles elicited are 50th, 25th, 75th, it is called quartile method (Morris et.al. 2014; O'Hagan et.al. 2006). The 50th percentile, $x_{0.5,}$ is known as the median and it divides the range of X into two equally probable ranges (with probabilities 0.5), where X is equally likely to lie above $x_{0.5}$ or below $x_{0.5}$. The lower quartile is the 25th percentile and the upper quartile is the 75th quartile. The quartiles and median divide the range of X into four equi-probable regions (with probabilities 0.25), hence the name quartile.

Software-based tools

Devilee and Knol (2012) reviewed usage of software packages to provide important support in expert elicitation, which includes support in collaboration of experts and building consensus, characterisation of uncertainties, selection of experts, design and execution of the process of estimation, and aggregation and reporting about outcomes. The quantitative estimates are often expressed in probabilistic terms (min, max, most likely values etc.) by the expert during the formal elicitation process which is carried out according to a protocol such as SHELF, SRI etc. and these estimates have to inform of a suitable probability distribution to be used as prior knowledge for root nodes. Features such as graphical support and interactive computing, are appealing in the use of software-based tools whilst eliciting probability distributions (Devilee and Knol, 2012).

MATCH Uncertainty Elicitation Tool is a free web-based probability elicitation tool to support elicitation of probability distributions about uncertain model parameters from experts Morris et.al. (2014). The tool originally provides a web-based interface for the SHELF elicitation package of Oakley and O'Hagan (2010) and is user-friendly, offers flexibility for the elicitation methods and also facilitates conduction elicitation remotely among geographically dispersed experts (Morris et.al. 2014). The tool offers five different techniques for eliciting univariate probability distributions, which include roulette method, quartile method, tertile method, probability method and hybrid method. It also fits various parametric distributions numerically, using the least squares procedure and report which distribution fits the expert judgements best.

2.4.3 Elicitation of Conditional Probability Distribution

BNs ability to express a comprehensive structure of uncertainty associated to a problem is widely recognised and has been widely addressed in literature, however assessing dependency between the uncertain variables has received less consideration whilst constructing BNs (Clemen et.al. 2000). Clemen et.al. (2000) also state that the final probability distribution of interest may be impacted by the level of dependency between uncertain variables and omitting dependency information may be trivial if the relationship between the variables is weak, but usually dependence can have a strong impact.

When expert judgement is used to determine the dependencies between variables due to lack of data (Clemen et.al. 2000), it permeates uncertainties in to BN and hence, it is important to understand the method employed for deriving conditional probabilities in the BN (Hansson and SJokvist, 2013). Deriving Conditional Probability Tables (CPT) with the aid of experts is no ordinary task. Das (2004) further elaborate the difficulties encountered in populating the CPTs. The distributions that are worked out successively tend to be consistent with each other. However, the problem arises about mutually consistencies when distributions further apart are assessed because experts lack a machine's uncompromising regularity. Most common effects on the expert are boredom and fatigue during the extended process. It will deter the uniformness of the criteria that is employed to figure out the distribution each time. Accompanied with these issues, is the time constraints with respect to the expert and their willingness to work through a large list of distributions, even if little time and effort is requested for each distribution. To overcome these issues, a number of methods have been suggested to elicit the conditional probability distribution in reasonable amount of time (Druzdzel and Van der Gaag, 1995). Elicitation of conditional probability is better than eliciting joint probability (O'Hagan et.al. 2006). Work of both prescriptive or descriptive in nature is limited on the assessment of dependence measures for modelling expert knowledge (Clemen et.al. 2000), especially methods are limited when a mix of continuous and discrete variables are present in BNs. Hansson and Sjökvist (2013) discuss likelihood method, EBBN method and weighted sum algorithm for the generation of complete CPTs which require minimal assessments from experts. Van der Gaag et.al (1999) proposed a probability elicitation method which involved transcribing probabilities for example, presenting conditional probabilities as fragments of text and using scale with both numerical and verbal anchors for marking assessments from domain experts, with an intention to elicit many probabilities in little time. They worked on eliciting conditional probabilities required to model an oesophagus influence diagram at the rate of 150-200 probabilities per hour. After reviewing literature, it was found that direct elicitation of conditional probabilities, EBBN method, likelihood method, weighted sum method and rank correlation method are the various approaches to derive CPTs. Rank correlation method further comprises of direct elicitation of rank correlation, statistical approaches, probability of concordance and conditional fractile estimates. These methods are described in Appendix A. Table 3 summarises some of the key features of the different used for elicitation of conditional probabilities.

Table 3: Comparison of Different Methods for Elicitation of Conditional Probabilities

Method	Time for Elicitation	Captures interdependence between parent nodes	Experts ease in providing dependency information
Direct method	High	Yes	No
EBBN	Moderate	Yes	Yes
Likelihood method	Low	No	Yes
Weighted sum method	Low	No	Yes
Rank correlation method	High/Low	Yes	No/Yes (depending on the specific method used for elicitation of rank correlation)

2.5 Research Gap Analysis and Conclusion

Literature review has identified the requirements to improve the understanding and quantification of uncertainties in PSS delivered in business-to-business application. Seven requirements were identified to address uncertainties prevalent in PSS, which are specified below,

1. Servitisation process leads to significant uncertainties in PSS and hence dictates a need to capture all the uncertainties.
2. System perspective in PSS dictates a need to capture the impact of relations between uncertainties on the quantified value of uncertainty of interest.
3. The need to understand uncertainty characteristics to support model-based decisions.
4. Forecasting in PSS with long lifecycle dictates the need to update forecasts in the light of

new information.

5. Compound effect of uncertainties and limited resources in term of cost, schedule etc. dictates the need to prioritise uncertainties.
6. The need to represent all uncertainties associated to supply and demand in the same model space.
7. The need to minimise loss generated because of conflicting goals in supply chains.

The first requirement highlights that servitisation leads to increase in the number of uncertainties and hence, solicits solution in terms of identification and definition of uncertainties in PSS. Requirement two is to understand uncertainty characteristics to provide model-based decision support and this could be achieved by mapping the two to understand what the uncertainty characteristics indicate that could aid in modelling decisions. Requirements from three to nine state requirements for treatment of uncertainty in terms of quantification. The modelling technique chosen to treat the uncertainty needs to capture relationships between uncertainties, update forecasts in the light of new information, capture compound effect of uncertainties, represent all uncertainties associated to supply and demand in the same model space and minimise loss generated because of conflicting goals in supply chains by capturing all the uncertainties related to the stakeholder performance metrics in the same model space.

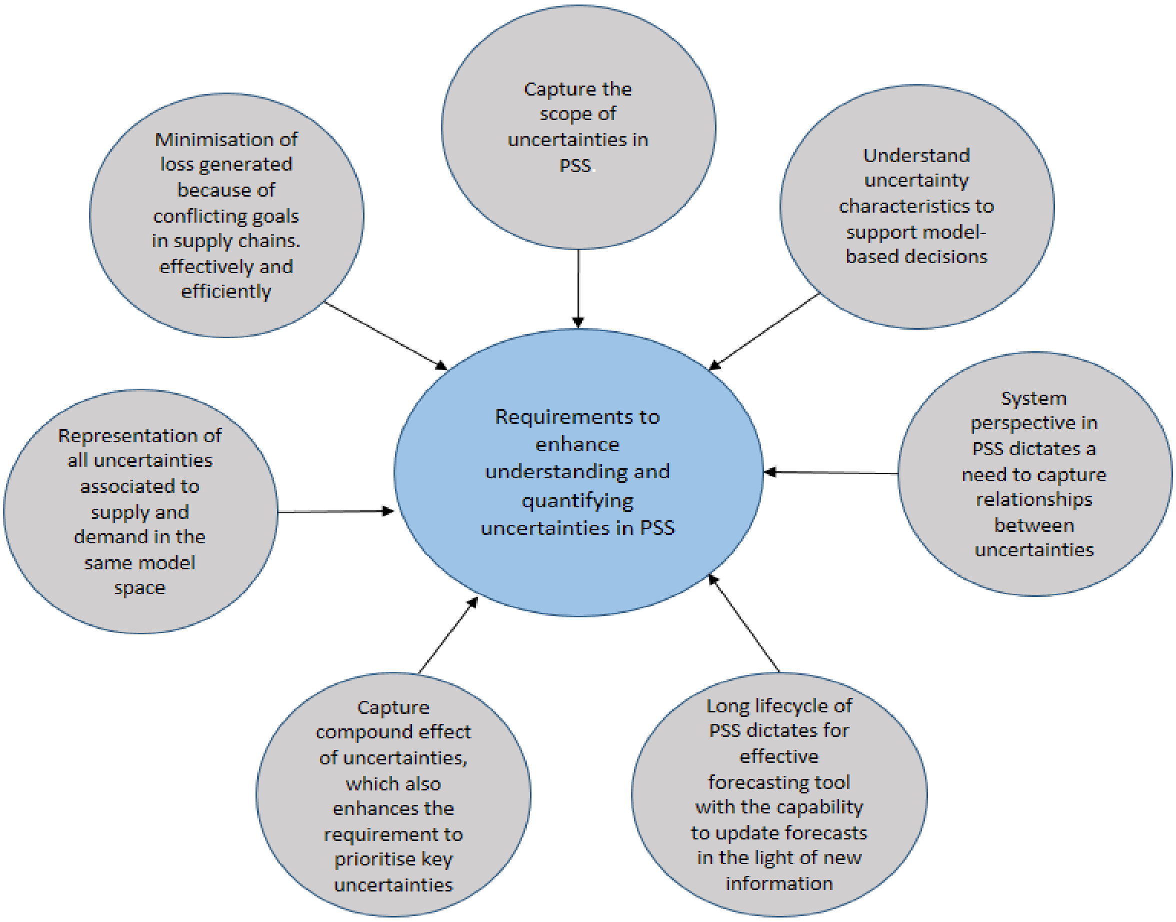


Figure 13: Requirements for Addressing Uncertainties in PSS

Figure 13 presents the requirements to be addressed to understand and quantify uncertainties in PSS that has not been addressed in current literature. Enhancement in understanding and quantification of uncertainties in PSS delivered in business-to-business application is the goal that needs to be addressed. Development of an uncertainty framework that could guide researchers and practitioners in industry in augmenting their knowledge as well as produce beneficial results would be a suitable solution. Thus, the uncertainty framework drawing on inference from all the requirements identified in literature review is presented in Chapter 3.

To conclude, in this chapter from Section 2.1 to 2.4 have presented existing work in relation to PSS, availability contracts, uncertainty and its various modelling techniques. The key element in Section 2.1 is the challenges encountered in PSS. The key challenges identified include increased scope of uncertainty, issues arising due to system perspective PSS brings along with it, issues due to the lifecycle approach in the adoption of PSS, issues arising with service in the lead role in PSS affecting balance between supply and demand and finally, issues surrounding decision-making in PSS. Section 2.1.2 on availability contracts, identified the key challenge was to achieve alignment between stakeholder goals and performance metrics. Section 2.2 reviewed various definitions of uncertainty and clarified the distinction between risk and uncertainty. Also a key element of this review, were the existing uncertainty classifications. It was also found that uncertainty and risk are two different concepts and this difference is adhered to, in rest of the research. The various classifications of uncertainty gave a picture of the purpose and usage of them. Many classifications impart knowledge of various uncertainty characteristics, however it was found that most classifications obtained was not put to practical use in a systematic manner. Section 2.3 reviews state of the art uncertainty modelling techniques implemented in PSS domain. Agent-based modelling, Analytical Hierarchy Process, fuzzy-based techniques and BNs were the recent tools and techniques applied to treat uncertainty in PSS. However, BNs were applied with an emphasis for cost estimation purposes rather than exploring uncertainty. Potential methods and approaches for developing BNs was looked into in Section 2.4. Hence, extensive literature review carried out presented a clear picture of the current state of research and the requirements to be addressed to understand and quantify uncertainty in PSS.

3 Uncertainty Framework

The framework is derived from analysis of industry requirements as well as literature.

The case study informed some requirements of industry for enhancing the delivery of PSS under availability contract arrangement in the face of uncertainty. These requirements overlapped to a large extent with the requirements identified from literature. Two requirements were identified from the interactions with industry during steering meetings, working meeting, industry visits and informal discussions. The industry representatives expressed their requirement as the "need for a crystal ball", which in other words is the ability to look into the future with the ability of clairvoyance. It was a key requirement in current state of affairs because of limited budget available for the customer to spend and the OEM is recognises that they could gain the contract only if they work within the constraints of the customer's affordability. Hence unlike the typical opportunistic scenario, it is the need for creation of win-win scenario where OEM aims to gain revenue and profit stream whilst keeping the customer budgetary constraints in mind. However, this is a challenge due to many uncertainties as discussed in Chapter 2. The second requirement expressed by level 1 supplier is the issues related to alignment or conflict between the stakeholder performance metrics as a significant factor whilst working under availability contract arrangement. The industry personnel agreed that several uncertainties are prevalent in availability contracts but emphasised on uncertainties particularly at the interface between organisations. Hence, it was identified that uncertainties need to be understood across the supply chain and how they affect the performance metrics of the stakeholders. In Chapter 2, seven requirements were identified from literature analysis and further supported by insights from industry. The requirements related to capturing the increased number of uncertainties and their relationships, understanding their characteristics, modelling techniques ability and ease to reflect results based on new findings, prioritisation of uncertainties, representation of all uncertainties related to supply and demand in the same model space and alignment between stakeholder performance metrics. It can be seen that the requirements expressed by industry are similar to and verify the findings from literature. The requirements enlisted above, was synthesised into the conceptual framework presented in Section 3.1. Requirements two, four, five and six was important in the selection of tools and techniques for handling uncertainty. The tools and techniques include the multi-layer uncertainty classification and the BN model. Understanding of uncertainty characteristics was realised by the multi-layer uncertainty classification. This approach to deriving the conceptual uncertainty framework is unique as it addresses the realistic requirements to treat uncertainties derived from industry and literature.

This chapter presents the conceptual uncertainty framework derived from requirements identified by reviewing literature and industry. Section 3.1 presents the uncertainty framework. The subsequent Section 3.2 presents the implementation of the framework to industry case study. Finally, Section 3.3 outlines the conclusions drawn from the chapter.

3.1 Conceptual Uncertainty Framework – Bird's Eye View

The conceptual uncertainty framework proposed in this research suggests that three factors need to be addressed in order to arrive at a holistic uncertainty solution. The three factors are set of uncertainties manifesting in PSS delivered in business-to-business applications, relationship between these uncertainties and the tools and techniques to treat these uncertainties. Discerning these three factors would enable one to arrive at a holistic solution, which enhances the management and analysis of uncertainty in PSS delivered in business-to-business applications. Each of these factors is explained below.

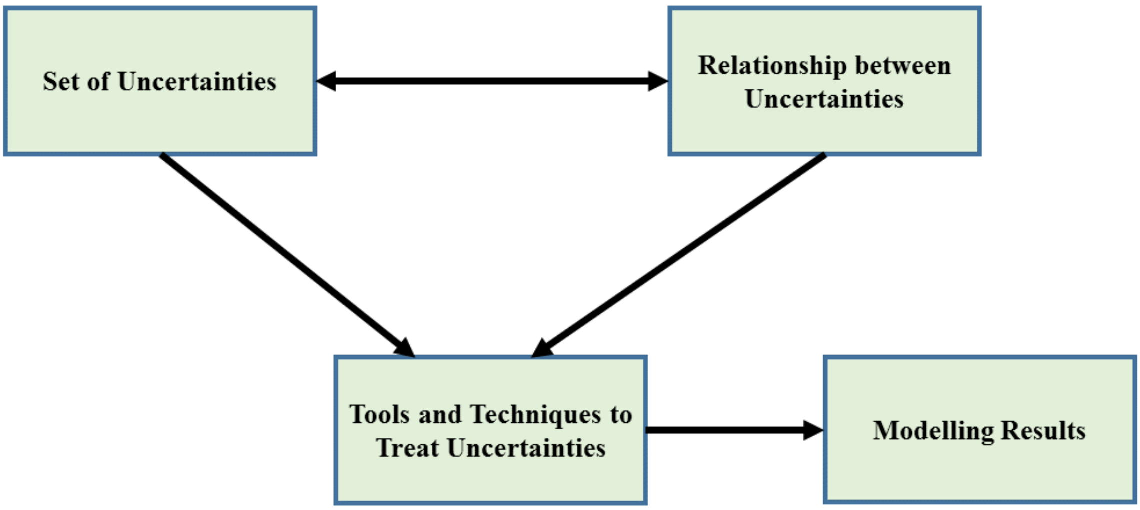


Figure 14: Uncertainty Framework – A bird's eye view

Set of Uncertainties

For uncertainty management and analysis, it is essential to recognise the uncertainties encompassed in PSS delivered in business-to-business applications. This element of the framework addresses the requirement to capture all the uncertainties in PSS as servitisation process leads to significant uncertainties in PSS. In trying to handle uncertainties, one needs to know first of all what kinds of uncertainties one is currently facing and also the future uncertainties, which adds to the complexity leading to a state where one is now uncertain about uncertainties (Grote, 2009). Hence, Grote (2009) suggests that the very first step is to define what one is looking for, that is to specify uncertainty.

The subjective and objective notions of uncertainty are significant (Zimmermann, 2000; Grote, 2009). There has been debate whether uncertainty is an objective fact related to the objective features of physical real systems or just a subjective impression, which is related to state of mind of humans (Zimmermann, 2000). The latter is the subjective interpretation of uncertainty depending on the quantity and quality of information, which is available to a human being about a system or its behaviour that the human being wants to describe, predict or prescribe (Zimmermann, 2000). Uncertainty analysis at best should include perception-based measures and objective indicators (Grote, 2009). Hence, it is beneficial to include objective and subjective accounts of uncertainty, while identifying and defining all the uncertainties embodied in PSS delivered in business-to-business applications.

Relationship between Uncertainties

As discussed previously, an appreciation of the variables, their definitions, how they can be manipulated and measured is of profound importance (Currier, 1979). This enables the researchers to identify independent and dependent variables and in turn their controllability (Lunsford, 1993). In order to identify independent and dependent uncertain variables, it is essential to know the relationships between the various uncertain variables. This element of the framework addresses the requirement to capture the relationships between uncertainties on the quantified value of uncertainty of interest, which is significant due to the system perspective adopted in PSS research.

Resource dependence and task interdependencies were prominent contributors to environmental and internal uncertainties respectively in organisations (Grote, 2009). And these uncertainties increase manifolds for organisations offering PSS, as resource and task interdependencies don’t just exist within the organisation but largely at the interface of boundaries of all organisations involved in delivery of PSS. The shift in the view of nature of organisations from closed systems acting more or less independently of their environment to its nature as open systems co-existing with and depending on their environment, hence environmental uncertainties have been a core concern (Thompson 1967). Pfeffer and Salancik’s (1978) prominent conceptualisation of organisations’ dependence on their environment centres on their dependence on resources from external partners with varying degrees of power as the core cause of uncertainties, for example, suppliers not providing information on anticipated late deliveries (Grote, 2009).

Internal uncertainties also known as task uncertainty (Van de Ven et.al. 1976) are described as various functions and operations in the organisation that can cause variability and unpredictability of work tasks, for example, such as insufficient quality of raw materials or machine failures (Grote, 2009). Task interdependence is a frequently discussed concept in socio-technical literature (Thompson 1967; Van de Ven et al. 1976). Typically three types of task interdependence are distinguished, which are pooled, sequential and reciprocal interdependence (Grote, 2009). Pooled interdependence is present when system performance is an additive function of individual performance, where performance of other members of the system may affect indirectly the work of the individual members, where subtasks are designed to serve the superordinate goal. An example would be a service organisation, such as an insurance company, where individual employees are responsible for all the concerns of a particular group of customers. Sequential interdependence is a unidirectional workflow arrangement, where individual performance depends on the proper fulfilment of prior subtasks. An example, of this kind of interdependence is the assembly line. In reciprocal interdependence, information and results of work activities have to be exchanged between team members continuously. Example for this interdependency would be project teams, which involves multiple parallel sources of uncertainties, such as misunderstandings about task requirements, changes in individual plans for task fulfilment or inadequate consideration of interfaces in project specifications. The interdependencies existing within resources and tasks indicate the high prevalence of relationships between uncertainties associated to each and between them. Hence, acknowledging the relationship between uncertainties is a key factor, when attempting to understand uncertainties and incorporating the impact of these interdependencies while quantifying the uncertainties.

Tools and Techniques to Treat Uncertainties

Several kinds of actors at various decision-making levels such as top management, middle management or shop floor personnel level have to be considered in order to understand how uncertainties affect decision-making in organisations (Grote, 2009). Grote (2009) point out that relevant sources and effects of uncertainties will differ substantially depending on the group of actors and types of decisions and actions required. Another aspect of decision-making is the conceptualisation of uncertainty which is studied either in terms of lack of information or lack of control over decisions and the different actions required for the achievement of organisational objectives because of reduced transparency, predictability and influence in terms of distribution of power within and across organisations and the competence level of the actors (Grote, 2009; Zimmermann, 2000; Flaming, 2007). Hence, the tools and techniques employed to treat uncertainties in order to support decision-making should be able to consider the different actors at various decision-making levels and incorporate both conceptualisations of uncertainty related to lack of information and lack of control in organisations.

Potential tool which could support decision-making under uncertainty in PSS delivered in business-to-business applications is an uncertainty characterisation tool, which sufficiently acknowledges and analyse uncertainty in decision support effort by appreciation of the various characteristics of uncertainty (Walker et.al. 2003). The uncertainty characterisation tool serves to support modellers in model-based decisions. It would support decision-making on the selection of experts who could help quantify uncertainty, decision on modelling the uncertainty with continuous or discrete data, decision on employment of further data collection methods for uncertainties are some of the decisions that uncertainty characterisation could aid in (see Chapter 5). There are various techniques proposed in literature to treat uncertainties such as Analytical Hierarchy Process (AHP), Agent-based modelling and fuzzy approaches (see Section 2.3). However, there are some requirements that the modelling technique needs to meet in order to model uncertainties in PSS robustly. Efficient updating of predictions in the light of new information is required as PSS have long lifecycles, during which new data may come into light. It should be able to capture the compound effect of uncertainties and prioritise uncertainties based on quantitative data as well as based on qualitative judgements elicited from experts. Able to represent all the uncertainties associated to supply and demand in the same model space and capture the concept of alignment of stakeholder goals in supply chains in order to minimise any loss generated because of conflicting goals. Bayesian Network is a potential modelling technique, which meets these requirements.

Modelling Results

The results expected would aid modellers and decision makers in analysing and managing uncertainties, especially the uncertainties arising during delivery of PSS. The overall aim of the framework is to initiate understanding of uncertainty in PSS and traverse towards quantifying them. Organisations involved in PSS especially delivered under availability contracts are required to make operational and strategic decisions and streamline their efforts in handling uncertainties, as they have performance measures to meet. Stakeholders forming value-networks is a significant component of PSS in business-to-business applications (Mont, 2004). However, there are only few studies which have systematically addressed different groups of actors in relation to management of uncertainty (Grote, 2009). The prediction of the probability of achieving the desired performance measures by the different actors in availability contracts and the configuration of different uncertainties affecting the respective performance measures are potentially useful results that could be obtained from the uncertainty framework proposed here. Decisions under uncertainty need to be taken, for example even for the design of a presumably straight-forward operational task that can involve strategic decision-making, such as decisions on production capacity etc. (Grote, 2009). The key contribution from the uncertainty framework proposed here, is a systematic procedure for identification, characterisation and modelling of uncertainties related to different stakeholders and their relationships. Hence, it can be summarised that knowing the uncertainties prevalent, interdependencies between them, characteristics and their measure all form the holistic uncertainty solution delivered from the uncertainty framework. It is believed that each of these elements are inseparable, as they are strongly inter-related.

3.2 Application of Uncertainty Framework – Worm's Eye View

The case study informed some requirements of industry for enhancing the delivery of PSS under availability contract arrangement in the face of uncertainty. These requirements overlapped to a large extent with the requirements identified from literature. This section presents an introduction to the case study used in this research, followed by the industrial scenario which is used to implement the conceptual framework and finally, the data collection methods employed in the case study.

3.2.1 Case Study

The provider of aircraft availability (BAE Systems) and one of its main suppliers (GE Aviation) are the two industries involved in the case study examined in this research (as shown in Figure 15). The former is addressed as 'OEM' and the latter as 'level 1 supplier' respectively in the rest of the thesis. Level 1 supplier is responsible for delivering availability of Multi-Functional Head Down Display (MHDD) which is installed in the Eurofighter Typhoon aircraft, under the arrangement of availability contracts with average repair Turnaround Time (TT) as the performance metric against which they are assessed. The OEM has the responsibility to ensure mission capability is achieved for a fleet of aircrafts to their customer. In this case study the exemplar used is an avionics equipment i.e. MHDD and not the whole aircraft or the fleet of aircrafts. MHDD is an electronic equipment, which has level 1 supplier as its OEM, which is GEA. Repair and maintenance of MHDD is the responsibility of GEA, which is made available to Royal Air Force (RAF) as drawn out in availability contract. GEA performance is assessed based on *Turnaround time* and BAE on the *Mission readiness* of a fleet of aircrafts. However, as focus of the industrial scenario is MHDD, *Equipment readiness* of MHDD is used as the performance measure for BAE. Considering only MHDD does not affect the research approach adopted, as the equipment is not core to PSS but the function delivered by it and therefore uncertainties affecting the function is of interest. MHDD could have 'Unserviceability' as its state when it is not in working order or not fulfilling its function adequately or unfit for use. It could be caused by a software failure or hardware failure.

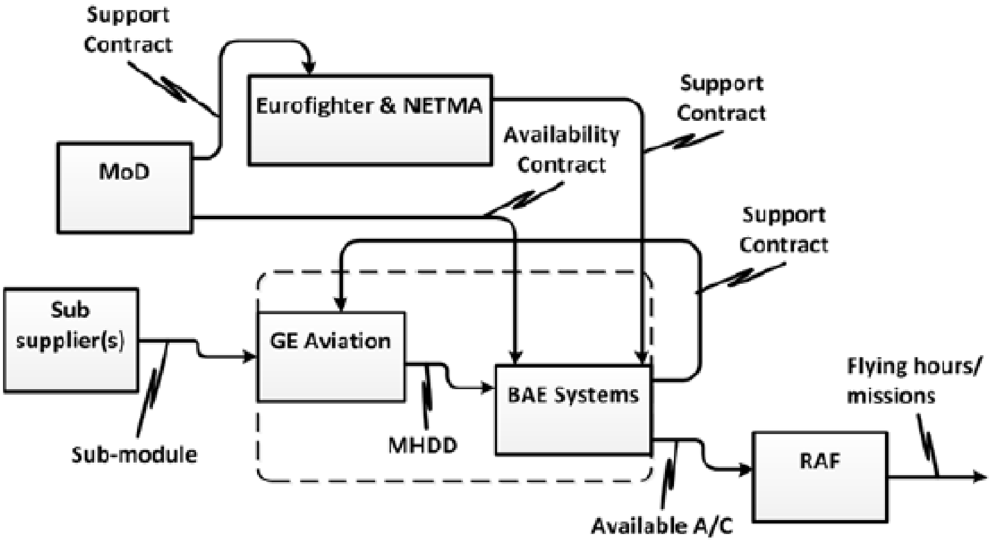


Figure 15 : Industries involved in the case setting- Unit of analysis lies within the dashed box (Thenent, 2014)

3.2.2 The Industrial Scenario

The industrial scenario considered is related to the delivery of serviceable MHDD to customer taking into consideration the uncertainties affecting the performance metrics of level 1 supplier and OEM. It is an instance of PSS delivered within the frame of availability contracting. The ownership of MHDD resides with level 1 supplier, who is the OEM for MHDD. However, the stakeholders are addressed according to their position in the supply chain with respect to the delivery of mission capability for a fleet of aircrafts, as discussed earlier, where original OEM of MHDD i.e. GE Aviation is addressed as 'Level 1 supplier' and the primary service provider i.e. BAE Systems is addressed as 'OEM'.

MHDD is a legacy equipment, which is quite well settled in the supply chain and the reliability of MHDD is forecasted fairly well. However, the state of MHDD is influenced by uncertainties related to customer handling, operating environment, etc. The customer pays for the usage of MHDD, which is calculated as number of operating hours and hence it is an application of use-oriented PSS. Level 1 supplier works with the customer, RAF and both parties strive to develop an innovative relationship between them to achieve common goals. Hence, the industrial scenario embodies the characteristics of PSS providing equipment-based service (Guo and Ng, 2011) and where the role of uncertainty in the execution of availability contract is very significant. Uncertainties about availability of various resources, uncertainty surrounding access of relevant information to all the stakeholders, uncertainty in prediction of service demand and uncertainties emerging due to contractual arrangement are some of the uncertainties faced in the industrial scenario described.

3.2.3 Data Collection

Data collection was initiated in January 2011 with the first meeting of the industrial collaborators and academics involved in the CATA project. The early data received from industry were mainly from presentations given by GE Aviation and BAE Systems contact personnel during formal project steering meets or more informal working meetings. In early 2014 the first semi-structured interview was conducted. Data was also collected from industrial documents received at early and mid-stages of the research and they were related to various aspects of MHDD such as model checklist, repair process, key performance metrics and excerpts from the FRCAS (Failure Reporting, Analysis and Corrective Action System) database, which enhanced understanding of the exemplar used in this research. Documents from industries are useful in gaining an early understanding of the topic that needs to be investigated (Noor, 2008). Documents are also a source of data that is important to supplement and compensate the limits of other sources (Noor, 2008). Questionnaires were used for data collection purpose, where the feedback received from it was used to validate and improvise the model structure.

The contact persons from BAE Systems and GE Aviation were also involved in co-ordinating and fixing interviews with personnel from their respective organisations. Five interviews were conducted spanning from an hour to two hours each. The interviewees were in job profiles ranging from director level to shop floor technician and they were all involved in activities affecting the delivery of MHDD availability to customer. The purpose of the semi-structured interviews conducted was elicitation of probabilistic and dependency information about uncertainties, which is discussed in detail in Chapter 7. The interviewees were forwarded with questionnaires and initial briefing material prior to the interviews. There were no ethical issues arising in the semi-structured interviews conducted in this research and all identities were anonymised. The group of interviewees who were interviewed was selected based on availability, their willingness to contribute to research and in this case ability to provide information of probabilistic nature. The information provided was not used for arriving at any consensus of any kind and hence, there was on bias in highlighting interests of any groups. However, there were no particular conditions placed on this work that would cause bias of any kind. No harm to the subjects of research was expected and neither did any negative consequences arise to the best of the author's knowledge. The consent for the research being carried was pre-defined in the parent CATA project and with further consent to be exercised before final submission of thesis. The interviews were recorded, however probabilistic and dependency information provided by the interviewees was written on the questionnaires. The experts were mainly queried for quantitative information. The elicitation for prior knowledge about all the uncertainties was carried out using SRI protocol, which consists of five steps such as motivating, structuring, conditioning, encoding and verifying (Spetzler and Stael Von Holstein, 1975 and Merkhofer, 1975).

3.3 Conclusions

The requirements identified from literature informed and motivated development of the conceptual uncertainty framework. It consists of four elements, which are set of uncertainties prevailing in PSS, relationship between these uncertainties, tools and techniques to treat these uncertainties and finally, modelling results of practical use. There are many conceptual uncertainty frameworks existent in literature, where most of them have not taken wings into practical implementation. However, the conceptual uncertainty framework proposed in this research is innovative in its ability for full-fledged implementation to a practical industrial application using a case study approach. However, the results have not been used to execute real decision-making in industry and this is out of the scope of this research. It could be future work that can be carried out. This can be seen in subsequent chapters, where each element of the conceptual framework has been implemented using an industry case study and potentially useful modelling results are obtained in the end.

4 Variables in Product Service System (PSS)

A pure product business model would typically have customer segment, key resources, key partnerships and cost structure. Whereas a pure service business model would have key activities, customer relationships, key resources and cost structure as the obvious elements. This shows that the number of elements considered in PSS is higher compared to business models offering pure product or pure service. One of the requirements identified from literature analysis was that servitisation process leads to large number of uncertainties in PSS and hence dictates a need to capture all the uncertainties (Section 2.5). Service characteristics such as intangibility, heterogeneity, inseparability and perishability would introduce additional uncertainties and hence identifying all the possible uncertainties is the first step towards understanding the role of uncertainty in PSS. If PSS in business-to-business applications is offered under a contractual arrangement, this induces additional uncertainties such as performance complexity, metrics, supplier reputation, negotiation cost etc. (Roy and Cheruvu, 2009; Caldwell and Settle, 2011 and Stremersch et.al. 2001). This chapter presents uncertain variables in PSS from a system perspective, which in total counts to 133 variables identified from literature. Section 4.1 presents the significance of distinguishing between variable and uncertainty and how variables are antecedents to understanding uncertainties. Followed by Section 4.2, which elaborates the steps adopted for identifying the variables. Finally in Section 4.3, conclusion and summary of the chapter is presented.

4.1 Variables - The antecedents to understanding uncertainties in PSS

There has been some research conducted on naming the uncertainties manifested in PSS (Phumbua and Tjahjono, 2010; Visnjic and Looy, 2011; Dean 2004; Erkoyuncu et.al. 2011; Matzen and Andreasen, 2006 and Kuo and Wang; 2012). Terms such as parameters, uncertainties and variables have been used in research referring to elements associated to uncertainty (Erkoyuncu et.al. 2011; Phumbua and Tjahjono, 2010 and Visnjic and Looy, 2011). Sometimes, variable and uncertainty have been used interchangeably (Swamidass and Newell, 1987). However, in this research, variable and uncertainty are defined differently. Variables are the individual elements that compose a system. The elements could be physical or abstract elements or ideas (Laszlo and Krippner, 1998) and this is reflected in the variables of both quantitative and qualitative nature extracted from literature. Re-iterating the definition of uncertainty as presented in Chapter 2, it refers to any deviation from the unachievable ideal of completely deterministic knowledge of a relevant system (Walker et al. 2003). Since variables constitute the system, any uncertainty associated with the whole system is bifurcated to the individual variables as well as to any impact from the relationships existing between variables constituting it.

An appreciation of the variables, their definitions, how they can be manipulated and measured is of profound importance (Currier, 1979). This enables the researchers to identify independent and dependent variables and in turn their controllability (Lunsford, 1993). Independent variables can be controlled directly, whereas dependent variables cannot be controlled directly. Variables aid in understanding the uncertainties manifested in different phases of PSS lifecycle such as design, development or delivery of PSS. For example, in designing of PSS the designers need to make sure that all the variables are considered and included in the construction of flow of events in providing service which needs to be modelled in the design phase itself (Morelli et.al. 2002). The transition from a traditional manufacturer to a service provider entails a lot more variables and an investigation into these variables impacts the success achieved in this transition (Bianchi et.al. 2009). Identification of variables is the first step towards visualizing the uncertainty manifesting in PSS.

In this research, variables are identified from a system perspective. This perspective is adopted because PSS itself has a system feature. This is reflected in the definition of PSS, which can be reckoned as presented in Chapter 2, where Goedkoop et.al. (1999) defines PSS as consisting of product, service and system element. PSS, uncertainty and variable all adopt definitions considering the system aspect and this reinforces the system perspective adopted for identifying the variables in PSS. Mont (2004) state that for successful implementation of PSS, organisations need to adopt a system approach, which allows for improved system variables and conditions. Variables typically discussed in literature are related to external demands and requirements (Mont, 2004). However PSS are inflicted by extraneous variables due to the integration of product and service offered as a single package. For example customer participation, equipment usage, retrograde time, operating environment etc. are the variables acting at the interface between product and service. The variables present at the interface between product and service play a critical role in PSS and needs to be dealt with, for successful design, development and delivery of PSS. Variable are antecedents to understanding the uncertainty in a system and hence it’s vital to understand what variables impact PSS.

4.2 Procedure for identification of variables

The procedure adopted for identifying the variables in PSS involves extensive search from literature and further analysis of the case study resulted in identifying the variables apt for describing the industrial scenario addressed in this research. Figure 16 represents the steps involved in identifying the variables and this is discussed in detail below.

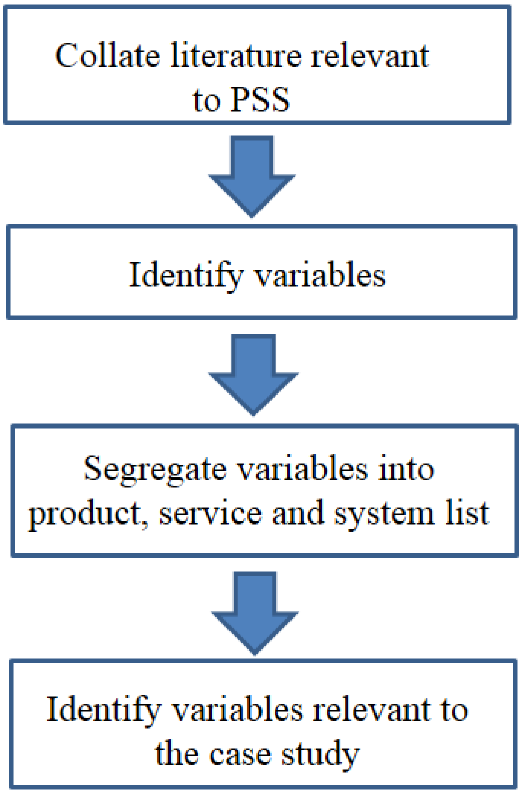


Figure 16: Flowchart for identification of variables

Step 1: Collate literature relevant to PSS

The source of literature included journal articles, conference proceedings, thesis, books, and reports. International journal of operations and production management, international journal of service industry management, journal of service management and CIRP provided access to a variety of publications from emerald, ebsco etc. The initial keywords were product service systems, maintenance management, performance-based contracts, supply chain, service and life cycle costing. However, the search was revised according to the results and was tested using a variety of key words. The distribution of references among the key topics is shown in

Figure 17. 45% of the references were from PSS, 17.5% from service and maintenance each, 10% from performance based contracts, 5% from supply chain and LCC each.

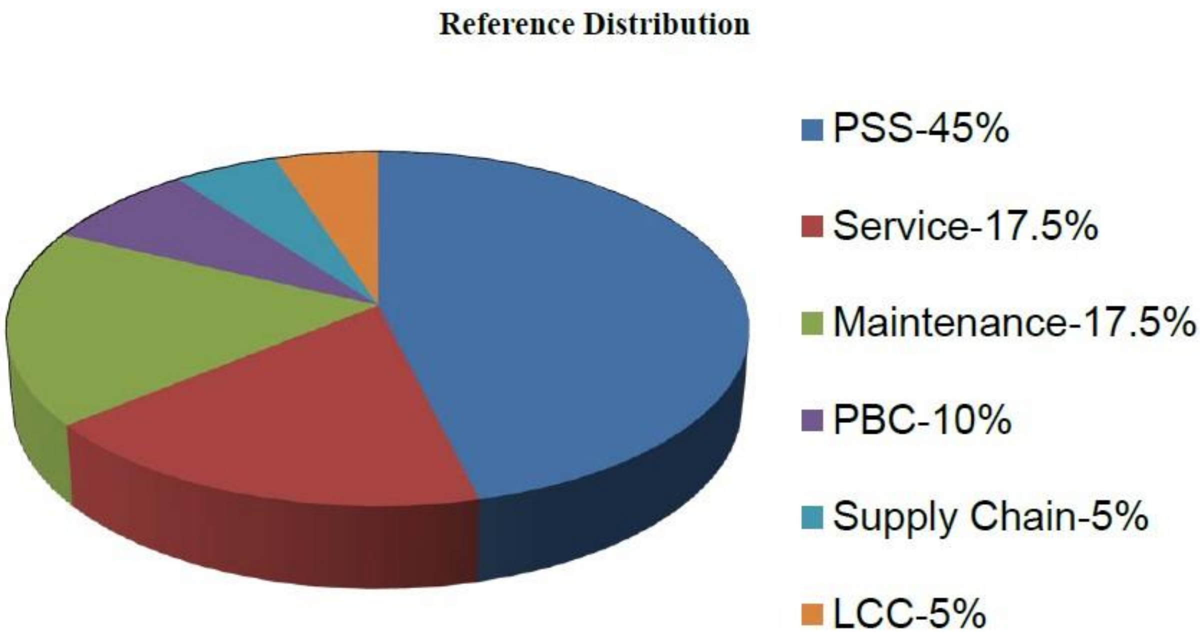


Figure 17: Reference distribution showing emphasis on service

During the identification of literature articles, there was emphasis placed on service and maintenance topics. This is due to greater impact of the role of service in PSS literature and also because operating and support costs form a significant proportion (up to 80%) of the total Life Cycle Cost (LCC) (Asiedu and Gu, 1998). In PSS, the objective of supporting the activities of the customer is considered predominant compared to the delivered products based on service dominant logic (Ng et.al. 2011). The emphasis on service is consistent with the need to minimise uncertainties in service design, which is important in PSS (Caldwell and Settle, 2011).

Step 2: Identify variables

The method used for identifying the variables in PSS is through an extensive targeted literature search and analysis. Although some literature on the variables and/or uncertainties in PSS was available, they were identified for modelling purposes (Bianchi et.al. 2009) or cost estimation purpose (Erkoyuncu et.al. 2011). These pre-determined purposes restrain the range of variables identified and an inclination towards variables of quantitative nature was observed.

Identification of variables was conducted using two methods, which are direct method and in-direct method. In direct method, the key word predominantly used in the search was 'variable'. A manual search of the relevant references was made by entering 'variable' in the find dialog box of the adobe software. Table 4 lists the variables extracted using this method along with the references.

Table 4: Variables identified directly

Variables	Reference
Qualification of the machine operator	Uhlmann et.al. (2008)
Degree of value co-creation; environmental variability; customer variability	Ng et.al. (2011)
Batch size	Cuthbert et al. (2011)
Pricing structure	Hockley et al. (2011)
Labour hours	Emblemsvåg (2003)
Number of service calls and visits	Hedge and Kubat (1989)
Changeover time (for production)	Leachman (1997)
Environmental variables (temperature and humidity, dust and entomological activities)	Oyebisi (2000)
Point of failure (threshold level of accumulated wear or damage)	McNaught and Zagorecki (2011)

Indirect method for identifying the variables was conducted primarily by deductive reasoning (Zhang and Wildemuth, 2009). Deductive reasoning was used to identify variables from existing theories presented in literature. Some of these theories include match between demand and supply (Sasser, 1976); availability or unavailability of product information to plan the maintenance ahead of time (Cuthbert et al. 2011) and characteristics of PSS motivating creation of new sources of added value and competitiveness such as deal with customer requirements in an integrated and customised way, building of unique relationships with customers and faster pace of innovation (Tukker, 2004). Different possible scenarios were hypothesised in the context of PSS based on theories stated in literature and enabled identification of the appropriate variables. It was also observed that the same variables were addressed using different terms by different researchers. For example, Service completion rate, System throughput, Volume of repairs/replacement, Number of service units delivered, number of service calls were different terms used to refer to the same aspect of service; degree of partnership, degree of subcontracting address the same aspect of contract; technical variables of product, number of components/sub-systems, product size address the same aspect of product; overflow and backorder address the same aspect of service.

The search was revised and a variety of key words were used according to the results. Initially, variables irrespective of their granularity were extracted. This was to ensure all the different elements of PSS are covered and to avoid any bias. Variables were refined and an attempt to arrive at a sensible and acceptable level of granularity for all the variables was endeavored. However, granularity of some variables was inevitably high, for example, supply chain visibility, work card design etc. This gave leeway to adhere to the generic nature of variables relevant to PSS and also facilitate any future research to dwell into greater detail of any variables of interest. As expected, more variables related to service than manufacturing was found. In total 133 variables were found, which were segregated into product, service and system lists. This is discussed in the next step.

Step 3: Segregate variables into product, service and system list

In this step the variables are enlisted and are segregated either into product, service or system list. The variables identified originated from different sources. They were customer-related, organisation-related, supply chain-related, contract-related, process-related and external factor such as macro-economic-related variables. The variables in system list were those that link product and service element of PSS. They primarily consisted of variables arising due to the interaction between product and service element of PSS. As can be seen from Table 5, the system list contains highest number of variables (81 variables) compared to product or service list. This result is consistent with the system perspective adopted in the identification of variables. 25 variables were enlisted in the product list and 27 variables were enlisted in the service list. The service variables are more in number compared to product variables. This exhibits the service emphasis placed during the search. It is also worth bringing to the attention, that conducting the search with emphasis on service has resulted in more number of variables falling into the system list. It indicates that variables related to service element have strong relations with the product element rather than has standalone service variables and hence position themselves in the system list of variables.

Table 5: Variables in PSS – Product list, Service list and System list

Variable	Reference
Product	
1) Batch size	Cuthbert et al. (2011)
2) Changeover time (for production)	Leachman (1997)
3) Cost of raw materials	Lockett et.al. (2011)
4) Cost of tool kit/ Consumables	Hedge and Kubat (1989)
5) Dates for design refresh	Romerorojo et.al. (2009)
6) Demand for spares	Nowicki et.al. (2008)
7) Effectiveness of diagnostics technology	Hedge and Kubat (1989)
8) Equipment efficiency	Oyebisi (1999)
9) Failure of software (including operating systems)	Romerorojo et.al. (2009)
10) Failure rate	Colen and Lambrecht (2010)
11) Mean time to failure (MTTF)	Oyebisi (1999)
12) Number of components/ sub-systems	Oyebisi (1999)
13) Occurrence of software obsolescence	Romerorojo et.al. (2009)
14) Occurrences of component/sub-system obsolescence	Romerorojo et.al. (2009)
15) Point of failure (threshold level of accumulated wear or damage)	McNaught and Zagorecki (2011)
16) Product architecture/ Type of product design	Ulrich (1995); Aurich et.al. (2006)
17) Product demand	Morris and Johnston, (1987), Emblesvag (2003)
18) Product size (width, height, weight etc.)	Oyebisi (1999); Brezet et al. (2001)
19) Production lead time	Sundin (2009)
20) Production volume	Komonen (2002)
21) Prototype cost	Romerorojo et.al. (2009)
22) Re-design cost	Romerorojo et.al. (2009)
23) Remaining useful life	Sandborn and Wilkinson (2007)
24) Re-manufacturing cost	Romerorojo et.al. (2009)

25) Total number of production personnel	Thorsteinsson (1995)
Service	
26) Availability of spares	Nowicki et.al. (2008); Finke and Hertz (2011)
27) Availability of test equipment	Tsai et.al. (2004); Wetzer et.al. (2006)
28) Availability of work bench	Hunter (1997)
29) Cost of diagnostic technology	Hedge and Kubat (1989)
30) Diagnosis time	Hedge and Kubat (1989)
31) Fitting of modification kits in the field cost	Romerorojo et.al. (2009)
32) Number of maintenance personnel	Drury (2001); Thorsteinsson (1995); Mjema (2002)
33) Overflow/ backorder	Hedge and Kubat (1989)
34) Queuing time	Shimada et.al. (2011)
35) Repair/replacement time	Finke and Hertz (2011)
36) Response time/ Reaction time/ Responsiveness (maintenance personnel)	Olorunniwo et.al. (2006); Finke and Hertz (2011)
37) Safety cases analysis cost	Romerorojo et.al. (2009)
38) Service completion rate/System throughput/ Number of service assignments completed per service technician	Baxter et.al (2009); Ang et.al. (2010); Finke and Hertz (2011)
39) Service coverage	Visnjic and Looy (2011)
40) Service demand/ Number of maintenance work orders/ Number of service assignments/ Number of service tasks	Bowen (1993); Mjema (2002); Finke and Hertz (2011)
41) Service location	Brezet et al. (2001); Finke and Hertz (2011)
42) Service operating efficiency	Chase (1981)
43) Service preparation time	Risku (2007)
44) Service recovery	Olorunniwo et.al. (2006)
45) Test time	Oyebisi (1999)
46) Training of the mechanic/ Training period/ Number of training sessions conducted	Romerorojo et.al. (2009); Pintelon and Gelders (1992); Mo (2012)

47) Type of service demanded	Finke and Hertz (2011)
48) Type of service failure	Mattila and Ro (2008)
49) Updates to documentation and training cost	Romerorojo et.al. (2009)
50) Verification & Validation cost	Romerorojo et.al. (2009)
51) Warehouses and repair vendors location/ Proximity of spare parts	Matamoros et.al. (2008); Finke and Hertz (2011)
52) Work card design	Drury (2001); Ip et.al. (2000)
System	
53) Administrative and customs' cost	Finke and Hertz (2011)
54) Attitude and behaviour of technician/ Stakeholder attitude	Finke and Hertz (2011); Roy and Cheruvu, (2009)
55) Availability of Back office/ Administrative personnel	Finke and Hertz (2011)
56) Availability of IT systems	Romerorojo et.al. (2009); Finke and Hertz (2011)
57) Availability of personnel (Production/ Maintenance)	Mjema (2002); Finke and Hertz (2011)
58) Contract escalation clauses	Roy and Cheruvu (2009); Crawford and Stewart (2010)
59) Cost efficiency	Caldwell and Settle (2011)
60) Cost of access to facility (Rent/ Lease)	Hedge and Kubat (1989)
61) Customer budget/ customer affordability	Bankole et al. (2009), Roy and Cheruvu, (2009)
62) Customer damage	Ng et.al. (2009)
63) Customer installed base visibility	Matamoros et.al. (2008)
64) Customer participation	Tax and Stuart (1997)
65) Customer satisfaction	Ang et.al. (2010); Finke and Hertz (2011)
66) Customer wait time (CWT)	Brauner and Lackey (2003)
67) Degree of subcontracting	Stremersch et.al. (2001)
68) Degree of value co-creation	Ng et.al. (2011)
69) Discount rate	Soti and Habing (2010)

70) Effectiveness of communication tools	Roy and Cheruvu (2009)
71) Efficiency of energy	Luxhog et.al. (1997)
72) Employee motivation	Luxhog et.al. (1997); Jonas et.al. (2009); Kinnison (2012)
73) Employee state(Physical health-illness, Fatigue Impact of personal events –family issues)	Drury (2001); Hobbs et.al. (2011)
74) Environmental variability/ customer variability/ Operating parameters (Operating environment)	Ng et.al. (2011); Mcnaught and Zagorecki (2011)
75) Exchange rate	Bankole et.al. (2011)
76) Facility design/ Infrastructure complexity	Caldwell and Settle (2011); Lewis and Roehrich (2009)
77) Human errors	Drury (2001); Finke and Hertz (2011)
78) Inflation rate	Soti and Habing (2010); Bankole et.al. (2011)
79) Infrastructural capability	Roy and Cheruvu (2009)
80) Intellectual property (Retention)/ Knowledge leak	Lockett et.al. (2011); Mo (2012)
81) Interest rate	Bankole et.al. (2011)
82) Labour cost / fee	Paz and Leigh (1994)
83) Labour hours	Emblesvag (2003);
84) Level of resource sharing	Meier and Funke (2010)
85) Level of Image/brand identity	Jonas et.al. (2009)
86) Level of technical skills/ Skill of the worker	Meier and Funke (2010); Drury (2001)
87) Level of cannibalisation	Johnson and Mena (2008)
88) Level of Confidentiality (exercised through policies/contracts)	Mo (2012)
89) Level of customer retention	Ang et.al. (2010)
90) Level of fit (product and service)	Hill and Cuthbertson (2011)
91) Level of knowledge maturity	Johansson and Ericson (2011)
92) Level of management support/ effort	Luxhog et.al. (1997)

93) Level of participation (customer)	Lockett et.al. (2011)
94) Level of technical knowledge	Baines et.al. (2007); Drury (2001)
95) Level of trust	Lockett et.al. (2011)
96) Safety stock	Roy and Cheruvu (2009)
97) Manpower (Employee) efficiency	Luxhog et.al. (1997)
98) Marketing performance	Ang et.al. (2010)
99) Negotiation cost	Roy and Cheruvu (2009)
100) Occurrence of process obsolescence	Romerorojo et.al. (2009)
101) Occurrence of skills obsolescence	Romerorojo et.al. (2009)
102) Performance complexity	Caldwell and Settle (2011)
103) Performance metric (Turnaround time/ Equipment readiness)	Vladimirova et.al. (2011)
104) Political climate	Bankole et.al. (2011)
105) Pricing structure/ Incentive design	Caldwell and Settle (2011); Hockley et al. (2011); Finke and Hertz (2011)
106) Public policies and Legislation Changes	Vladimirova et.al. (2011); Bankole et.al. (2011)
107) Quality of support	Drury (2001)
108) Relationship cost	Tukker (2004)
109) Relative importance of stakeholders/ Node criticality	Li and Liu (2010), Craighead et.al. (2007)
110) Renegotiation cost	Roy and Cheruvu (2009)
111) Renewal period	Albano et.al (2006)
112) Requisition wait time (RWT) / Order and Ship Time (OST)	Brauner and Lackey (2003)
113) Resource workload	Meier and Funke (2010)
114) Retention of intellectual property	Lockett et.al. (2011); (Mo, 2012)
115) Retrograde duration	Parlier and Greg (2005)
116) Share prices	Bankole et.al. (2011)
117) Size of customer base	Ang et.al. (2010)

118) Size of installed base	Colen and Lambrecht (2010)
119) Source of fill (also known as "fill source")	Brauner and Lackey (2003)
120) Speed of innovation	Tukker (2004)
121) Supplier reputation	Stremersch et.al. (2001)
122) Supply chain visibility/ Information visibility	Matamoros et.al. (2008); Du et.al. (2012)
123) Supply complexity	Caldwell and Settle (2011)
124) Task complexity	Pintelon and Gelders (1992)
125) Transport system reliability/ Resource transition/transport time	Meier and Funke (2010); Hedge and Kubat (1989)
126) Unexpressed customer demand	Ng et.al. (2011)
127) Variation of the assets utilisation/ Change of usage patterns/ Utilisation rate of production machinery/ Equipment usage	Emblesvag (2003), Mo (2012)
128) Work force stability	Drury (2001)
129) No Fault Found	Hockley and Phillips (2012)
130) Operating experience	Meier and Funke (2010)
131) Qualification of the machine operator/ Employee competence	Uhlmann et.al. (2008); Jonas et.al. (2009); Drury (2001); Mjema (2002); Mo (2012); Ang et.al. (2010)
132) Quantity of the life-time buy	Romerorojo et.al. (2009)
133) Re-certification against regulatory requirements cost	Romerorojo et.al. (2009)

Step 4: Identify variables relevant to the case study

The deductive reasoning initiated in step 2 is further followed in this step in order to hypothesise and confirm the variables relevant to the industrial scenario adopted for implementation of the conceptual uncertainty framework presented in Chapter 3. The observation of activities in the case study led to the confirmation of relevant variables. Table 6 presents the variables identified as relevant to the case study from the list presented in step 2.

Table 6: Variables Relevant to the Case Study

Variables relevant to the case study
1. Availability of personnel
2. Availability of spares (at level 1 supplier facility and customer facility)
3. Availability of test equipment
4. Availability of work bench
5. Customer damage
6. Degree of sub-contracting
7. Demand for spares (contractor and in-house spares)
8. Equipment readiness
9. Equipment usage
10. Failure rate
11. Infrastructural capability
12. Intellectual property
13. Level of confidentiality
14. Level of skill and knowledge
15. No fault found
16. Operating environment
17. Production lead time
18. Quality of support
19. Remaining useful life
20. Requisition wait time
21. Retrograde duration
22. Safety stock
23. Service demand
24. Service personnel efficiency
25. Supply chain visibility
26. Task complexity

27. Transport time
28. Turnaround time

The case study focuses on delivering availability of MHDD under the arrangement of availability contracts with *Turnaround Time* (TT)) as the performance metric against which level 1 supplier is assessed and *Equipment Readiness* (ER) is the performance metric the OEM is striving to achieve. An understanding of different activities engaged in by the industrial collaborators in the delivery of MHDD was obtained through information provided by industry personnel's at various occasions. Discussions of both formal and informal nature took place during industry visits, steering meetings and working meetings that took place at the different university premises collaborating in the CATA project, OEM facility and also in the level 1 supplier facilities. The steering meetings were conducted at an interval of 2 to 4 months, since 2011. Steering meetings were attended by the three industry contact personnel's representing the customer, OEM and level 1 supplier as well as all the academics and researchers of the CATA team. Working meetings were conducted to identify and represent all the activities involved in the delivery of MHDD. Initially all the researchers in the CATA team, proposed a representation of the primary activities identified in the case study by their choice of method. The author used cross functional flow chart (Figure 18) to represent the activities and IDEFO maps were developed by other members of the CATA team. The flowchart described is "cross-functional" which means the page is divided into different swim lanes describing the control of different organisational units such as Customer, level 1 supplier and OEM. A symbol appearing in a particular "lane", for example stock (inverted triangle), an event such as MHDD arising (rectangle), is within the control of that organisational unit. This technique allows the author to locate the responsibility for performing an activity or making a decision, involved in the MHDD delivery process. As can be seen from Figure 18, MHDD arising is under customer swim lane. This triggers Acceptance Test procedure in the level 1 supplier swim lane and subsequently other events which come under the responsibility of different stakeholders. An analysis of the cross-functional flowchart confirmed the relevance of the variables to the case study. These variables were observed to best describe the case study at hand.

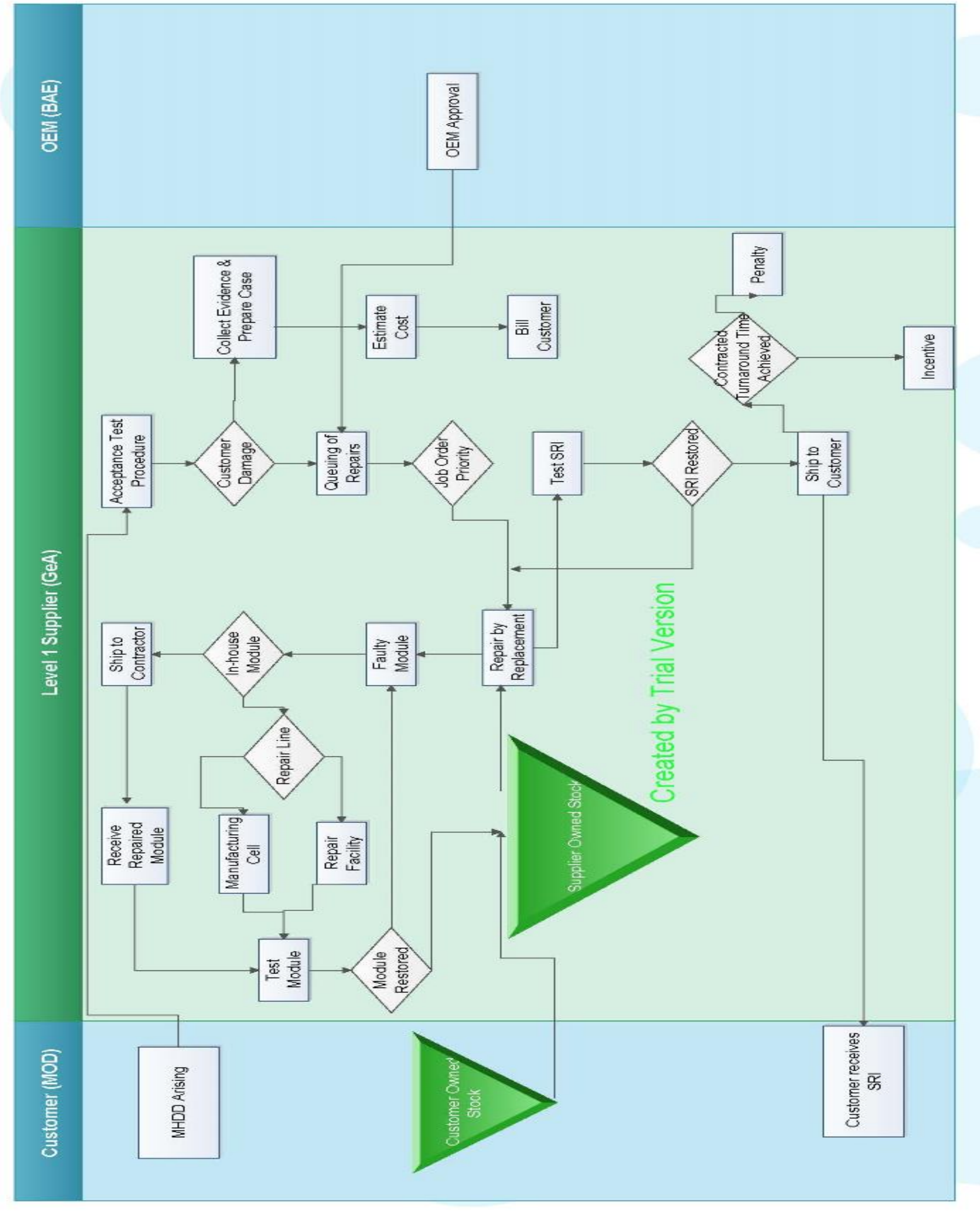


Figure 18: Cross-Functional Chart of the Activities for providing MHDD Availability

As can be seen from Figure 18, type of spare (referred to as ‘Shop Replaceable Item’ SRI or MHDD module in industry) could be either in-house manufactured or contractor supplied. Hence, demand could be for in-house spares or contractor spares. This distinction of demand based on the type of spare requested is essential as they have different set of variables affecting them. It was also found that MHDD failure was increased due to damage caused by customer handling and it usually resulted in hardware or physical damage of MHDD. Hence *Customer damage* was another variable identified. *Quality of support* rendered by the suppliers upstream in the supply chain impacts the supply chain visibility of level 1 supplier. If the supplier has a competitive attitude towards the recipient supplier, it hinders visibility of information flow in the supply chain. An organisations inclination towards retention of intellectual property impacts the manner in which service is provided for a failed MHDD. *Retrograde duration* causes piling of failed MHDD and they are transported at bulk to the service provider, which induces a surge in service demand. In PSS attention on forecasting the demand for service is important, which was traditionally not considered or undermined by manufacturers as equipment uptime was not their responsibility. And also the service recipient or customer is an external factor who needs to be considered in the provision of service (Uhlmann et.al. 2008). Variables such as *Retrograde duration* and *Intellectual property* play a pivotal role in triggering service demand. Hence, organisations providing equipment-based services integral to the PSS in business-to-business offering have to understand and incorporate these variables in computing service demand. In the case study adopted, the customer is Ministry of Defence (MOD), who requires the equipment to function in challenging circumstances. The *Operating environment* could be a normal training of the pilot, where the operating parameters such as temperature, vibration, humidity etc. are at normal levels. Whereas, in a combat operating environment these operating parameters could deviate from their optimum values and be deranged. This would have effect on equipment reliability and therefore is a potential uncertainty in the industrial scenario considered. A combat could also result in heavy usage of the equipment and hence, the number of operating hours reflecting customer usage needs to be considered. *Remaining useful life* is another uncertainty which would be crucial in determining equipment reliability in such adverse circumstances. *Failure rate* is an uncertainty which gives a means to measure equipment reliability and this is recorded and analysed by industries to forecast equipment reliability.

When *Degree of contracting* increases, in other words as the number of subcontractors working in the supply chain increases, it hampers the degree of visibility of information flow.

There are many suppliers involved in manufacturing, delivering and maintaining MHDD's and hence degree of contracting is an uncertainty to be considered. *Level of confidentiality* is induced when huge industries are involved as in the case considered here. Contracts are drawn between the industrial collaborators placing constraints in information shared and other vital issues. *Infrastructural capability* is an uncertainty which would affect the number of repairs performed at the customer facility. Inadequate tools, material and work place would result in failed MHDD to be transported to the supplier facility and this increases repair time. Hence, customer and the supplier has to make decisions on the tradeoffs between enhancing infrastructure at the customer base or shipping it to supplier for repair, which would be strategic decision affecting the manner in which service demand is met. *Supply chain visibility* is an uncertainty relevant because of the existence of large number suppliers and sub-suppliers in the supply chain. The mere number of suppliers poses an obstacle for information flow and transparency. Hence, when demand for a contractor supplied spare arises, the supplier may not have information enough to forecast demand beforehand and hence supply chain visibility is an uncertainty affecting spares in terms of its availability and time required to make it available from the time it is ordered. From this interlinking of uncertainties, it can be seen that availability of spares and requisition wait time are other uncertainties relevant to the case study. In order to meet with surge in demand for in-house manufactured spares, it is essential to maintain a safety stock at the supplier site. In the case study adopted, it was found that *No Fault Found (NFF)* instances were recorded for performance assessment. Availability contracts were designed to ensure that a turnaround time of 30 days was met. Hence, uncertainties such as skill and knowledge of maintenance personnel, task complexity and service personnel efficiency would impact performance. Availability of resources such as personnel, test equipment and work bench are other uncertainties on the supply side required to meet and support service demand. Transport time of spares to customer facility is an uncertainty to considered especially with suppliers distributed globally in the case study. *Turnaround time* and *Equipment readiness* are the two performance metrics perceived as vital uncertainties which need to be dealt with under availability contracting in the case study.

4.3 Summary and Conclusion

133 variables were identified in literature pertaining to PSS. There was additional emphasis placed on the service whilst searching for variables and this is reflective in the selection of references. Identification of variables in PSS fills the gap in literature, by expanding the scope

and increasing depth to which uncertainties in PSS are considered. Variables identified here is believed to be comprehensive capturing the product, service and system element of PSS.

It is of interest to acknowledge that emphasis on service resulted in extracting higher number of variables that could be categorized and enlisted in the system list. This is consistent with the system perspective adopted. Identification of variables from a system perspective provides a broad overview without limiting to any context or intended usage of the variables but rather to capture all the possible elements of PSS that could be prospective uncertainties. The system perspective also sheds light on the impact of customer related variables such as equipment usage, operating environment, customer damage, retrograde time and customer participation of PSS in triggering demand for service.

5 Development of Multi-Layer Uncertainty Classification

This chapter presents a multi-layer uncertainty classification for characterising uncertainties. The main purpose of this classification was to encapsulate as a tool, which would enhance understanding uncertainties in PSS and support modelling decisions whilst quantifying the uncertainties. Hence, it is an implementation of the tool element of the conceptual uncertainty framework presented in Chapter 4. This chapter is structured as follows. Section 5.1 addresses the procedure followed to derive the multi-layer uncertainty classification. Section 5.2 elaborates the various uncertainty characteristics forming the multi-layer uncertainty classification. Section 5.3 presents application of the multi-layer classification to case study uncertainties. Finally, Section 5.4 outlines summary and conclusion drawn for the chapter.

5.1 Method for Developing Multi-Layer Uncertainty Classification

The method adopted for developing the multi-layer classification involved analysing the literature and understanding similarities and differences between different typologies presented. In the light of inference drawn from the characterisation process and observation of all the uncertainties identified (Chapter 4) and the existing uncertainty characteristics mentioned in literature, a new multi-layer uncertainty classification was developed. One key literature analysed for this purpose was the five layer uncertainty classification proposed in the area of competitive bidding for offering PSS in business-to-business application (Kreye et.al. 2011). This served the primary purpose of understanding some of the characteristics of uncertainty. The method adopted to enhance a detailed understanding of some the uncertainty characteristics was conducted by a three step procedure, which includes propagation of uncertainties, characterisation of uncertainties and inferring on some of the characteristics of uncertainty to be included in the new multi-layer uncertainty classification. All the uncertainties identified relevant to the case study was propagated through the five layer uncertainty classification (Kreye et.al. 2011). Then the uncertainties were characterised using the five layers. The newly developed multi-layer classification is expansive and addresses wider number of uncertainty characteristics. It consists of uncertainty characteristics such as nature, context, decision level, scale, effect, cause and source, which further have sub-classifications, as shown in Figure 19.

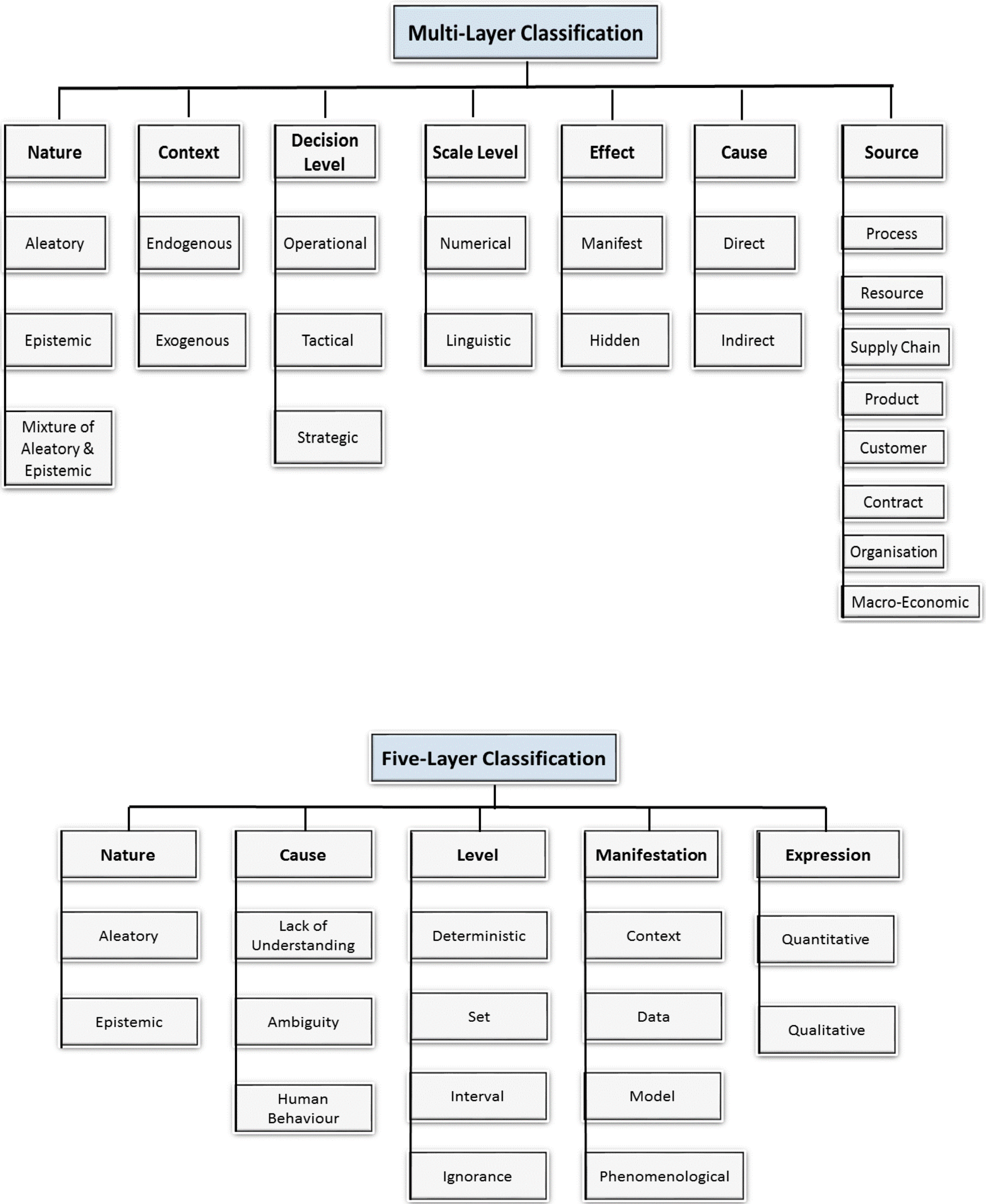


Figure 19: Multi-Layer Classification and Five-Layer Classification

a) Propagation of Uncertainties

A reference thematic framework reflects key issues, concepts and themes, which is subject to further refining at subsequent stages of analysis ((Ritchie and Spencer, 1994; Srivastava and Thompson, 2009) and in this case the five layer uncertainty classification proposed by Kreye et.al (2011) was adopted . The focus here is to refine the reference five layer uncertainty classification and to obtain a detailed insight into some of the characteristics of uncertainties in PSS. This refining is not an automatic or mechanical process but calls for logical and intuitive thinking, where judgements about meaning, relevance and importance of issues and about implicit linkage between ideas need to be made (Srivastava and Thompson, 2009). In order to achieve this in a transparent and objective manner, the uncertainties are propagated through the five layer classification. Characterisation of uncertainties is the next step involved in developing the multi-layer classification.

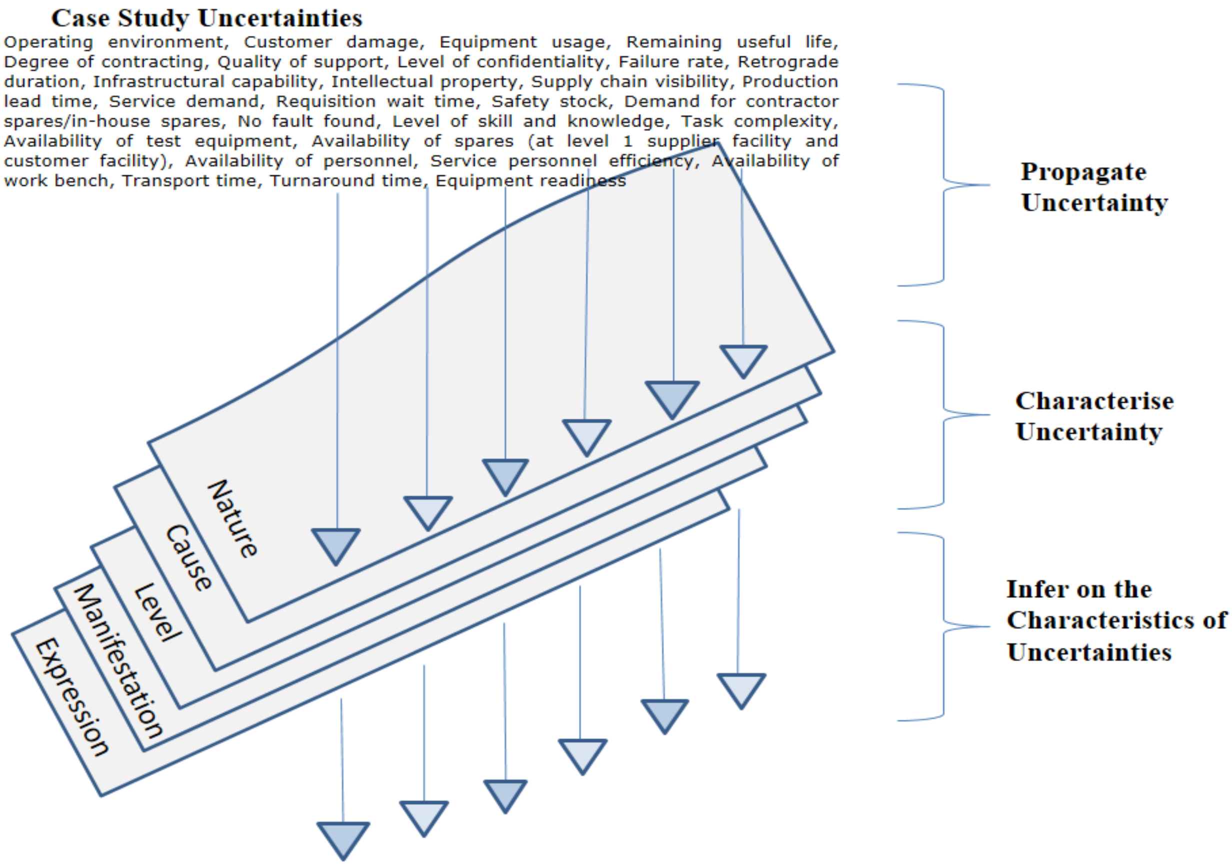


Figure 20 : Characterisation of Uncertainties Using Five-Layer Classification

b) Characterisation of Uncertainties

In this step, each uncertainty is dwelled upon in detail to specify each of the characteristics as in the five layer uncertainty classification, which are nature, cause, level, manifestation and expression. Nature refers to the general characteristics of uncertainty, where inherent variability is called as aleatory uncertainty or a general lack of knowledge called as epistemic uncertainty. Cause is the reason or source of the uncertainty. Uncertainty can be caused by a lack of understanding, ambiguity and human behaviour. Level refers to the severity of the uncertainty, i.e. the amount of information available and the amount of information missing for a certain description of the situation. Manifestation refers to the point of the process where the uncertainty occurs. Expression is the way the uncertainty is articulated or communicated. It can be quantitative (measurable) or qualitative (unmeasurable). Context uncertainty in manifestation layer includes endogenous uncertainties and exogenous uncertainties. Endogenous uncertainty are under the control of the organisation in terms of decision making or other explicit actions to deal with them. Exogenous uncertainties reside outside the boundary of the system or product and is not under the control of the organisation. Data uncertainty is related to input into a system or model, which could be due to data incompleteness, data inaccuracy and variation in the data. Model uncertainty is the difference between the model and the reality, which the model intends to represent. It usually results due to the simplification of the model to facilitate computation or limited data availability. Phenomenological uncertainty arise due to unknown unknowns or the possible behaviour of a system or events which has not been thought of. Even if they are known, unpredictability of their occurrence is another issue. A snapshot of this characterisation is presented in Table 7. The complete characterisation of all the case study uncertainties can be found in Appendix D. Inference is drawn about uncertainty characteristics to be included in the new classification after characterising all the case study uncertainties. This is the next step in developing of multi-layer classification.

Table 7: Snapshot of Characterisation using Five-Layer Classification

Characterisation Of Uncertainties Using Five Layer Classification					
Uncertainty	**Nature**	**Cause(Lack of understanding, Ambiguity, Human behaviour)**	**Level(Deterministic, Set, Interval, Ignorance)**	**Manifestation(Context, Data, Model, Phenomenological)**	**Expression (Quantitative, Qualitative)**
Availability of spares (at level 1 supplier facility and customer facility)	Epistemic	Lack of understanding (Lack of information, Imprecision); Ambiguity (Conflicting evidence); Human behaviour (Human errors, Changes in personnel)	Set/ Interval	Endogenous/Exogenous; Data (Incompleteness, Inexactness, variation); Model (Mathematical, Computational); Phenomenological	Quantitative
Customer damage	Epistemic/ Aleatory	Lack of information; Ambiguity (Lack of definition, Conflicting evidence, Poor communication process)	Interval	Exogenous; Data (Incompleteness, Variation); Model (Mathematical, Computational)	Quantitative
Equipment usage	Epistemic	Lack of understanding (Lack of information); Ambiguity (Lack of definition, Conflicting evidence), Human error	Interval	Exogenous; Data (Incompleteness, Inexactness, Variation); Model (Computational)	Quantitative

c) Infer on Characteristics of Uncertainties

It consists of inference drawn from analysis of the uncertainty characteristics described above as well as generic observations from existing uncertainty characteristics mentioned in literature. Characterising using the five layer classification led to the following inference. Most of the uncertainties were characterised with epistemic nature and some were even classifiable as having both epistemic and aleatory nature not included in the five layer classification. Lack of understanding especially due to lack of information was found to be the primary cause of the uncertainties. The level of knowledge about the many of the uncertainties could be represented as interval of possible alternatives. The context of majority uncertainties were endogenous, which is obvious because of the Level 1 supplier perspective (GeA) adopted in the characterisation exercise. However, a few uncertainties could not be classified as exogenous or endogenous clearly as they were found to be at the interface of organisation boundaries. For example, degree of contracting uncertainty was within the level 1 supplier control for in-house manufactured modules of the MHDD. But the degree of contracting done by suppliers and sub-suppliers in the upstream supply chain for contractor manufactured modules was not under the control of level 1 supplier. Many uncertainties would be manifested with variation form of data uncertainty, where different alternatives may be plausible as input values. This could be reasonable because of the increased subjectivity and uniqueness of the uncertainties involved in PSS. Choosing of the appropriate computational model seemed to be the model uncertainty involved. Most of the uncertainties could be expressed quantitatively.

The primary focus of the five-layer classification was intended to understand some of the characteristics of uncertainty. The five layer uncertainty classification is an extension of Walker et.al (2003) three dimensions of uncertainty of nature, level and location. Reckoning the purpose of multi-layer uncertainty classification was to support model-based decisions. In order to support this purpose, nature uncertainty characteristic was retained but modified to include uncertainties that have a mixture of aleatory and epistemic nature. It was also found that characteristics such as nature and cause were recurring uncertainty characteristics mentioned in existing literature (Kreye et.al. 2011; Erkoyuncu, 2011; Walker et.al. 2003; Thunnissen, 2003). The cause characteristic was modified for different sub-categories to suit the purpose. In the uncertainty framework presented in Chapter 3, it was discussed that relation between uncertainties was significant. Hence, in line with this causal relation between uncertainties are classified into direct and indirect cause. The context characteristic was retained, however its sub-categories has been modified as some uncertainties were characterised to have their context of origin in between endogenous and exogenous context. Hence endogenous was further classified into inter and intra organisational context. Level of uncertainty referred to different levels of severity in Kreye et.al. (2011) classification. However, here scale level refers to the manner adopted to express uncertainty. This modification also describes level of severity to higher level above that described in five layers. Here numerical scale level indicates a lower level of severity where uncertainty is closer to quantification and linguistic level indicates a higher level of severity where uncertainty is still described linguistically, which means further away to precise quantification. Cause and source were used interchangeably by Kreye et.al. (2011), however in this research it is believed to be two different terms with different meanings. Cause refers to the thing that gives rise to an action, phenomenon or condition, whereas Source means a place, person, or thing from which something originates. Hence, here source of an uncertainty could be a process, resource, supply chain, product, customer, contract, organisation or macro-economic factor. These were enlisted by observing all the uncertainties identified and they all originate from either of the sources. Additional characteristics such as decision level and effect were also introduced in the multi-layer classification in order to distinguish between different levels of decisions and the kind of effect the uncertainties emanate.

5.2 Multi-Layer Uncertainty Classification

Pursuing the method described above, a multi-layer uncertainty classification was developed from literature, observation of the existing classifications and PSS uncertainties identified in Chapter 4. The main purpose of this classification was to provide a tool, which would enhance understanding uncertainties in PSS and support modelling decisions whilst quantifying the uncertainties. The multi-layer uncertainty classification consists of seven characteristics, such as nature, context, decision-level, scale level, effect, cause and source (Figure 21). These are discussed in detail below and an example of its applicability in supporting model-based decisions especially while using BN modelling technique is presented in Section 5.3.

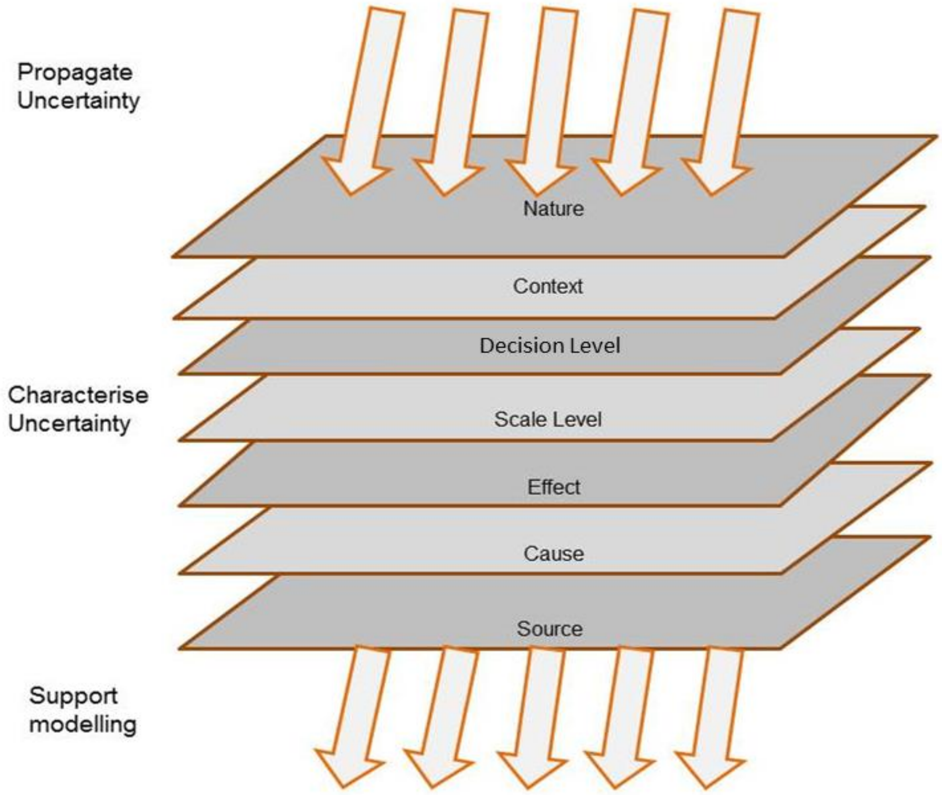


Figure 21: Multi-Layer Uncertainty Classification

1) Nature – Aleatory, Epistemic, Mixture of Aleatory and Epistemic

The nature characteristic could be further classified as aleatory or epistemic or mixture of aleatory and epistemic. Aleatory uncertainty is defined as the uncertainty due to inherent nature of the system. It is also referred to as irreducible uncertainty. Epistemic uncertainty is due to the lack of knowledge or information about the system. An uncertainty is a mixture of aleatory and epistemic uncertainty, when some portion of it is represented as probability distribution and some portion is represented as interval (Oberkampf et.al. 2010).

The representation of uncertainties varies depending on whether their nature is epistemic, aleatory or mixture of epistemic and aleatory. Aleatory uncertainty is almost certainly represented as a PDF and epistemic uncertainty is represented as interval (Oberkampf et.al. 2004). Roy and Oberkampf (2011) present some additional options to represent the uncertainties depending on their nature. They suggest that aleatory uncertainty could be represented as CDF, which quantifies the probability that the uncertainty will be less than or equal to a certain value. Hence, a precise probability distribution is used to represent aleatory uncertainty. Whereas, an epistemic uncertainty is represented as an interval with no associated PDF or as a PDF which expresses the degree of belief of the expert. They further shed light on uncertainty characterised as a mixture of aleatory and epistemic could be represented as an imprecise probability distribution, where interval-valued quantities for the parameters such as mean, standard deviation etc. of the distribution is elicited from experts.

By distinguishing the nature of uncertainty into either of the three categories will give an indication as to which uncertainties need further information from experts and potentially reducing effects of the specific uncertainty. And also acknowledging the uncertainties which are intrinsically varying and irreducible, and special cases where some portion of the uncertainty can be reduced by gaining further information and some portion is irreducible due to its aleatoric nature.

2) Context – Endogenous (Intra and Inter-Organisation), Exogenous

It was found that many uncertainties cannot be assigned clearly as internal or external to the OEM who delivers PSS in business-to-business application bound contractually. This can be attributed to the system issues in contracting where the customer and supplier come inside the systems boundary in a complex setting that is non-linear and highly dynamic and much more

is accomplished for both parties by working closely (Ng et al. 2009). To address this issue, endogenous context should be further sub-divided into inter and intra-organisational context (Figure 22). Inter and intra-organisational context, makes distinction between uncertainties which emerge and hence be managed by the OEM solely (intra) or uncertainty arising due to close collaboration of OEM, suppliers and/or customer and requires a cooperative effort to mitigate the uncertainty (inter). Uncertainties outside of the PSS are classified as exogenous uncertainties, where inflation rates, exchange rates etc. are examples of such uncertainties.
Acknowledging the context characteristic of uncertainty supports modelling by identifying the specific stakeholder/stakeholders who can influence the uncertainty and hence predominantly contribute towards controlling and managing the uncertainty. It also facilitates a clear visual of inter-playing and dependence between different uncertainties associated to different stakeholders.

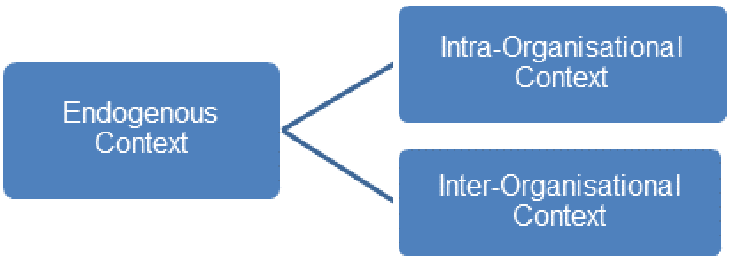


Figure 22: Endogenous Context of PSS in business-to-business application

BN clearly shows the dependence between uncertainties and characterising them by the context to which they belong helps to identify the linkage between different stakeholders. Hence, the key uncertainties active at the interface between stakeholders is highlighted. A further benefit of characterising the context of the uncertainty is identification of the source of data or information for the uncertainty to derive prior probabilities in BN. In complex PSS offering such as availability contracting, 100's of sub-contracts are executed by many stakeholders and hence this multiplicity of stakeholders creates a complex network with multiple uncertainties. Characterising the context of a specific uncertainty pinpoints the source/sources of information by identifying all the stakeholders who have a stint in influencing or controlling the uncertainty. It could provide further details by specifying the name of the organisation under inter-organisation context, if the number of sub-contractors are numerous. Prior probabilities can be obtained from all the stakeholders involved and integrated for uncertainties in inter-organisational context. Further, if a certain uncertainty ranks high in sensitivity analysis, further information needs to be collected to refine the modelling outcome and knowing the context of the uncertainty facilitates acquisition of data related to the uncertainty.

3) Decision level - operational, tactical or strategic level

It gives an indication as to whether the uncertainty of interest is viewed at the operational, tactical or strategic level. Hence, categorising it as strategic, tactical or operational decision variable and facilitates to direct efforts at the right management level to manage and control the uncertainty.

ECOGRAI is an approach developed at the GRAI laboratory for measuring performance of the organisation, which states that for each organisation a set of decision variables are defined (Jagdev et.al. 2004). The approach states that the management performs actions upon the decision variables and this guarantees that the objectives defined for the organisation are achieved. Objectives for organisations can be defined at strategic, tactical and operational levels and it is possible to define a set of decision variables for each of these level respectively (Jagdev et.al. 2004). Decision variables can be witnessed as vital to an organisation. This characterisation would aid in identifying whether the uncertainty is a decision variable as well as knowing the decision level at which the uncertainty can to be viewed would aid in directing effort from the appropriate management level. This perspective of the uncertainty also specifies the management level at which the uncertainty is influential and hence initiate coping plans. This could be useful in developing influence diagrams, which are an extension of BNs by modelling uncertainty as decision variables.

4) Scale level – Numerical, Linguistic

Scale level refers to the manner adopted to express uncertainty. Probability distribution with a mean value and variance represents a numerical approach to uncertainty (Kreye et.al. 2011; Dubois et al., 2003). These are termed numerical scale level in this research. Uncertainty can also be expressed in a linguistic way, for example in informal communication (Dubois et al., 2003) and are termed as linguistic scale level. Characterising the uncertainty into numerical and linguistic, helps in identifying the uncertainty as a discrete or continuous node in the BN modelling. Typically, if an uncertainty is described at the numerical scale level, it would be modelled as a continuous node in the BN. Whereas, if an uncertainty is described at the linguistic scale level, it would be defined as a discrete node in the BN.

5) Effect - Manifest, Hidden

The uncertainties whose effects are observable have information available as data records or expert judgement and are characterised as manifest. As the term manifest indicates, it refers to an uncertainty which is readily perceived and evident. Hidden variables are not represented in the data (Ramachandran and Mooney, 1998). Hidden variables also known as latent variables are variables for which one has no observations, but one suspects it exist and can be useful for modelling the real world (Norsys, 2014). Incorporating latent or hidden variables is a crucial aspect of modelling, as they provide a succinct representation of the observed data through dimensionality reduction, where many observed variables are synthesised by few hidden variables (Anandkumar et.al. 2012). The effect considered here is emanating from the uncertainty itself and not manifested in a separate uncertainty.

Characterising the uncertainty based on whether the effect produced by the uncertainty is observable or not observable supports in specifying some nodes as hidden or observable node in BN modelling. Hence, it can be said that characterising uncertainty as to whether it produces effect which is observable or unobservable indicates the modelling decision of the choice of algorithm or the method to be chosen for learning the hidden nodes of the BN. For example in Netica, one can use EM (Expectation Maximisation) algorithm or gradient descent learning to learn hidden nodes (Norsys, 2014). If all uncertainties are characterised as having manifest effect, there is regular learning occurring in the BN model, else special algorithms are executed to quantify the hidden uncertainties. Characterising the effect of uncertainty as manifest or hidden, alerts the modeller about the existence of any hidden nodes in the BN that is learnt from data. This is important as not acknowledging the existence of hidden nodes, will result in wrong reasoning and inference of the results from the compilation of BN.

6) Cause – Direct, Indirect

It is widely acknowledged that the distinction between direct and indirect causation is important (Spohn, 1990). The causal influence of one event on another is direct, if it is not mediated by other events in between and otherwise it is indirect (Spohn, 1990). This characterisation supports the modeller in building the BN structure, which is the qualitative element of BN modelling (Renooij, 2001) and induces transparency in the decisions taken whilst building the network.

Markov blanket is a useful concept in BNs, which refers to a node's parents, its children and its children's parents (Korb and Nicholson, 2003). The node which is attributed as a direct cause of a reference node is modelled as the parent node. The node without parents is called a root node and a node without children is called a leaf node (Pearl, 1988; Korb and Nicholson, 2003). Any other node (non-leaf and non-root node) is called an intermediate node (Korb and Nicholson, 2003). Any node characterised as an indirect cause of a reference node is modelled as an intermediate node. Characteising an uncertainty as a direct or indirect cause of another uncertainty of interest supports the modellers decision to attribute the node as a parent node or intermediate node while building the BNs. Once the parent nodes and intermediate nodes are known, it is relatively easier to position the root nodes and leaf nodes

Therefore, characterisation of the uncertainty as a direct or indirect cause of a reference uncertainty unveils the structure of the BN by presenting all the variable relationships. The modeller could use this information and build the structure of the BN. It could be seen as analogous to putting together a jigsaw puzzle. The relationship between a pair of uncertainties as the puzzle pieces and the BN analogous to the whole puzzle picture.

7) Source - Process, Resource, Supply Chain, Product, Customer, Contract, Organisation, Macro-economic

Understanding the source of uncertainty is considered as a profound aspect in uncertainty management (Ward and Chapman, 2003; Gosling et.al. 2013). Characterisation of uncertainty ascertains whether expert elicitation is a relevant approach to deal with uncertainties (Knol et.al. 2010).

Characterisation of uncertainty based on the source from where it originates supports modelling activity in selecting the experts for quantifying the uncertainty of interest. Quantifying the uncertainty in order to specify the prior probabilities of all the nodes in the BN is essential (Druzdzel and Van der Gaag, 1995). The prior probabilities can be quantified by the data available as historical records or by probability elicitation using experts (O'Hagan et.al. 2006). In order to use expert judgement, it is important to select suitable experts as they can greatly affect its outcomes (Gordon, 1994). Some criteria's to select experts include the following (Senior Seismic Hazard Analysis Committee, 1997).

1. Strong relevant expertise through academic training, professional accomplishment and experiences and peer-reviewed publications;

2. Familiarity and knowledge of various aspects related to the issues of interest;
3. Willingness to acts as proponents or impartial evaluators;
4. Availability and willingness to commit needed time and effort;
5. Specific related knowledge and expertise of the issues of interest;

As can be seen from the list, expertise and knowledge are key criteria's to be satisfied by the experts chosen for probability elicitation. Characterising the source of uncertainty maps to the different realms of the organisation and this enables to identify the work area or areas the experts need to be from. For example an uncertainty such as diagnosis time arises in the service process and hence an expert working in service should be chosen to elicit probabilities. Source of uncertainty gives a clear indication of the expert job profile or profiles required. Table 8 comprehends the different sources of uncertainties in relation to PSS, which was derived from literature. These were primarily identified by observing the uncertainties identified in Chapter 3. The uncertainties were assignable to the source or sources from where they originated.

Table 8: Categories and Sub-categories of Sources of Uncertainty

Sources-Category	**Sub-Categories**
Process	Design, Manufacturing, Service, Disposal
Resource	Information, Human, Hardware, Software
Product	Product type, Product upgrades, Product performance
Supply chain	Supply chain planning, Procurement, Supply chain integration, Logistics
Customer	Affordability, Demand
Contract	Bidding, Payment system, Contract renewal

Organisation	Infrastructure, Policy, Competition
Macro-economic	Legislative, Politics, Inflation

Loveridge (2004) classifies three types of professional experts, who are generalists, subject-matter experts and normative experts. Generalists usually have substantial knowledge in a relevant discipline and a solid understanding of the context of the problem. Hence, they are suitable for expert elicitations about context or model structure uncertainties and where the topic is multidisciplinary. Subject–matter experts are deft in their field of expertise. They are the prime experts from whom judgements are often elicited and they are apt to provide subject specific information such as model parameters. Normative experts, have knowledge, practical experience or skills that can support the elicitation process itself. Their role could be equivalent to a facilitator's role in probability elicitation (Oakley and O'Hagan, 2010). Decision analysis, statistics or psychology are examples of the areas they could be specialised in. They could provide support when thought processes are challenging or when the format of the elicited information requires insight into probabilities or heuristics. Generalists and especially subject-matter experts can be identified in the organisation, once the domain or domains associated to the uncertainty is known. Hence, characterising the uncertainty based on the source from where they arise in a vast domain such as PSS is extremely useful.

After understanding the uncertainty characteristics and obtaining their contribution towards supporting uncertainty modelling decisions, the next step towards implementing the uncertainty framework involves applying BN modelling technique to treat the uncertainties. This stage quantifies the uncertainty and provides numerical graphical representation of the uncertainties in PSS, which is discussed in the next chapter. Before that, application of the multi-layer classification to case study uncertainties is looked into in the subsequent section. This allows to understand the uncertainties better by acknowledging their different characteristics and their implications on modelling activity.

5.3 Application of the multi-layer classification to support BN modelling

The multi-layer uncertainty classification, which is discussed above is used to characterise the uncertainties, which would be used in the BN modelling. Chapter 4 presented the variables in

PSS and 30 variables among them relevant to the case study were used as potential uncertainties to build the BN.

Table 9: Snapshot of characterising uncertainties using multi-layer classification

Uncertainty	Nature	Context	Decision Level	Scale Level	Effect	Cause	Source
Service demand	Epistemic/ Mixture of aleatory and epistemic	Inter-organisation/ Exogenous	Operational/ Strategic	Numerical	Manifest	Direct (eg. Direct influence on Availability of spares_2 in BN)	Product/ Supply chain/ Customer
Degree of sub-contracting	Aleatory	Inter-organisation/ Exogenous	Strategic/ Operational	Linguistic	Manifest	Direct (eg. Direct influence on Supply chain visibility)	Contract/ Organisation
Quality of support	Epistemic/ Aleatory	Inter-organisation/ Exogenous	Tactical/ Operational	Linguistic	Latent	Direct (eg. Direct influence on Supply chain visibility)	Customer/ Supply Chain
Level of confidentiality	Epistemic/ Mixture of epistemic and aleatory	Inter-organisation/ Exogenous	Strategic/ Tactical	Linguistic	Latent /Manifest	Direct (eg. Direct influence on Supply chain visibility)	Customer/ Supply chain/ Macro-economic
Supply chain visibility	Epistemic/ Mixture of epistemic and aleatory	Inter-organisation/ Exogenous	Strategic/ Tactical	Linguistic	Latent/ Manifest	Direct (eg. Direct influence on Requisition wait time)	Supply chain/ Customer

This section presents characterisation of the uncertainties and how this characterisation process aided in making model-based decisions in BN modelling technique. Figure 21 presents the multi-layer uncertainty classification discussed in Section 5.2 and the propagation of uncertainties to characterise and support BN modelling decisions is demonstrated by an example here. Table 9 presents a snapshot of the characterisation process for a sample of the uncertainties used in BN modelling. Characterisation of all the uncertainties is presented in Appendix D.

The characterisation of Service demand provides the following suggestions to BN modelling. Nature of Service demand could be epistemic or a mixture of aleatory and epistemic. It could be represented as a probability distribution that represents degree of belief of the expert or as an imprecise probability distribution. Context of the uncertainty indicates, that the sources for data or further information about Service demand could be an organisation in the supply chain network or external to the organisation like the customer. Service demand could be a decision variable at the operational or tactical or strategic level of the organisation. Scale level of Service demand indicates that it would be represented as a continuous node in the BN. Effect character indicates that Service demand is observable and modeller doesn't have to expect any latent effect from the uncertainty itself. Cause characterisation of Service demand identified it as a direct cause/influence for the uncertainties such as availability of spares, availability of personnel, availability of workbench and hence it could be their parent in the BN structure. Source characterisation of Service demand suggests that experts be chosen who have expertise about product, supply chain and/or customer.

The above discussion on relating the uncertainty characteristics to BN modelling shows the application of the multi-layer uncertainty classification to support BN modelling. The extent to which characterisation of the uncertainty supports BN modelling depends on the clarity with which the characterisation process is carried out by the analyst or modeller. If the analyst has a clear understanding of the uncertainty and the context/application in which it is characterised and arrives at single alternative for each of the characteristics in the multi-layer classification, the outcome from the characterisation could be used straight away for BN modelling. In other situations, characterisation provides the different options available to the modeller whilst building and quantifying the BN.

5.4 Conclusion and Summary

The conclusion drawn from this chapter is the relevance and insights provided by the various characteristics of uncertainty to provide model-based decision support. In literature, many uncertainty characterisation schemes have been proposed. They are developed for a specific problem area and no consensus has been established towards a standard classification even within a specific discipline. Some of the classifications are proposed for decision making, product design, project management and modelling in general. The uncertainties in each area are different in terms of the way they are measured, modelled and dealt with and hence, they will require a characterisation scheme specific to the modelling method or application. On the other hand, some characteristics such as cause, nature may be applicable to uncertainties in many research areas. Hence, the author is convinced that uncertainty characterisation schemes have to be tailored to the specific modelling technique at hand. The uncertainty classification adopted may differ slightly based on the theory the modelling technique is based on. For example, all modelling techniques based on probability theory may be sufficiently addressed by the same uncertainty classification with slight modifications. A multi-layer uncertainty classification is proposed to aid BN modelling and would be the key contribution of this chapter. The five-layer uncertainty classification of Kreye et.al. (2011) and analysis of existing uncertainty classifications aids in the development of multi-layer uncertainty classification. The classifications consists of the following characteristics: nature (Epistemic, Aleatory, Mixture of epistemic and aleatory), context (Inter-Intra organisation, Exogenous), decision level (Strategic, Tactical, Operational), scale level (Numerical, Linguistic), effect (Manifest, Latent), cause (Direct, Indirect) and source (Process, Resource, Product, Supply chain, Customer, Contract, Organisation, Macro-economic). It is a novel approach in uncertainty characterisation as it provides support to decision-making in the modelling process in a pragmatic manner. This is mainly by providing suggestions to various decisions the modeller is faced with.

6 Structure of Bayesian Network

BN was identified as potential modelling technique to treat uncertainties For the industrial scenario of the case study adopted in this research, the structure of BN is derived from expert knowledge and literature. This chapter is structured as follows, Section 6.1 presents some fundamental theory underlying BN modelling technique such as probability theory, Bayes rule, chains rule and conditional independence is presented. Insights from literature and industry are the main sources of knowledge used in deriving the structure of BN and these are discussed in Section 6.2 and 6.3 respectively. Section 6.4 presents merging of findings from literature and industry to derive the final BN structure. Section 6.5 presents face validity test conducted to validate the BN structure. Likert scale scoring was used for this purpose and this is discussed here and the questionnaire related to validation presented in Appendix B. Section 6.6 presents the assumptions underlying the BN structure. Section 6.7 outlines the summary and conclusion of the chapter.

6.1 Theory of Bayesian Networks

Graphical models have been discussed in literature, among which BNs have attracted much attention from scientific community (Morales, 2010). It is a method for reasoning under uncertainty using probability theory, where a set of variables and their relationships are represented as nodes and directed edges (Jensen, 1996). Determining the structure of BN and population of the Conditional Probability Tables (CPTs) are the two phases involved in building BNs (Park and Cho, 2012). Identification of variables and their dependencies are the two eminent steps in building the structure of BN (Lucas et.al. 2013). Probability theory, Bayes' rule, Chain rule, conditional independence and d separation are fundamental to the theory of BNs. These are presented in subsequent paragraphs as they would enhance ones understanding of theory underlying BNs.

Bayes' Rule

A sample space Ω is defined as a set of outcomes that is, Ω= $\{\omega_1, \omega_2, \omega_3, \ldots \omega_n)$.

An event E on Ω is subset of Ω, that is, E⊆ Ω. From this point of view, outcomes may be seen as elementary events, that is, events that can only take on a true/false character. Events are things which we might be interested in and tend to be the fundamental unit of probability theory. A probability distribution P, is a function from the space of events to the space of real numbers from 0 to 1, that is,

$P : \mathbf{P}(\Omega) \rightarrow [0,1]$, where $\mathbf{P}(\Omega)$ is the power set of **Ω**.

Since events are sets, we can perform set operations on them. This allows us to specify the probability of two events, *E* and *F* occurring, by $P(E \cap F)$. From this we can define another very useful idea, that of conditional probability.

The conditional probability of an event E occurring, given that an event F has occurred is given by

$$P(E|F) = \frac{P(E \cap F)}{P(F)} \dots \dots \dots (1)$$

($P(E \cap F)$ is also written as $P(E,F)$)

For this to be defined, P(F) must be strictly positive. Also it should be noted that,

$$P(E \cap F) = P(E|F)\, P(F) = P(F|E)\, P(E)$$

This implies that,

$$P(E|F) = \frac{P(F|E)P(E)}{P(F)} \dots \dots \dots (2)$$

This is the well-known Bayes' rule and is fundamental to BNs. The term P(E|F) is often known as the posterior probability of E given F. The term P(F|E) is often referred to as the likelihood of F given E and the term P(E) is the prior or marginal probability of E.

Chain Rule

Re-arrangement of the formula for conditional probability (1) would result in a rule called chain rule. This rule is especially significant for BNs, as it provides a means of calculating the full joint probability distribution.

$$P(E,F) = P(E|F)\, P(F)$$

We can extend this for three variables:

$$P(E,F,G) = P(E|F,G)\, P(F,G) = P(E|F,G)\, P(F|G)\, P(G)$$

and in general to n variables:

$$P(E_1, E_2, \dots, E_n) = P(E_1| E_2, \dots, E_n)\, P(E_2| E_3, \dots, E_n)\, P(E_{n-1}| E_n)\, P(E_n)$$

In BNs many of the variables E_i will be conditionally independent which means that the formula can be simplified as shown below. Suppose the set of variables in a BN is $\{E_1, E_2, \dots, E_n\}$ and that ***parents***(E_i) denotes the set of parents of the node E_i in the BN. Then the general case of joint probability distribution in BN for $\{E_1, E_2, \dots, E_n\}$ is:

$$P(E_1, \dots\dots, E_n) = \prod_{i-1}^{n} P\big(E_i \big| parents(E_i)\big) \dots\dots\dots (3)$$

Conditional Independence

Defining a joint probability distribution across many variables $P(E_1, E_2, \ldots, E_n)$, would require to store 2^n -1 values, if each variable is binary valued and this increases the storage requirement exponential to the number of variables, things soon would become intractable (Daly et.al. 2011). Conditional independence eases the number of values required to define joint probability distribution, as explained below.

$$P(E_1, E_2, \ldots, E_n) = P(E_1 | E_2, E_3, \ldots, E_n)\, P(E_2, \ldots, E_n)$$

Now, if $E_1\ {}_1\perp\!\!\!\perp_p \{E_{3,\ldots\ldots} E_n\} | E_2$, which means if E_1 independent of the rest of the variables give E_2. Then,

$$P(E_1, E_2, \ldots, E_n) = P(E_1 | E_2)\, P(E_2, \ldots, E_n) \ldots\ \ldots\ \ldots (4)$$

The expression involving E_1 has become much shorter and a slightly smaller joint term Daly et.al. (2011). Finding conditional independencies for rest of the variables would lead to factorisation that can proceed in a chain like fashion and would be left with product of a small number of random variables. Therefore, to construct the joint probability distribution, specifying few number of conditional probability distributions (Daly et.al. 2011). D-separation is a criterion for deciding, from a given BN, whether a set *E* of variables is independent of another set *F*, given a third set *G.*

D-separation

Bayesian networks encode the dependencies and independencies between variables. Under the causal Markov assumption, each variable in a BN is independent of its ancestors given the values of its parents and using this assumption, we can check some conditional independence in BNs. For the general conditional independence in a BN, Pearl (1988) proposed a concept called d-separation. D-separation is a graphical property of BNs and has the following implication: If two sets of nodes E and F are d-separated in BN by a third set G (excluding E and F), the corresponding variable sets E and F are independent given the variables in G. The definition of d-separation is as follows: two sets of nodes E and F are d-separated in BN by a third set G (excluding E and F) if and only if every path between E and F is “blocked”, where the term “blocked” means that there is an intermediate variable V (distinct from E and F) such that:

- The connection through V is “tail-to-tail” or “tail-to-head” and V is instantiated
- Or, the connection through V is “head-to-head” and neither V nor any of V’s descendants have received evidence.

The graph patterns of “tail-to-tail”, “tail-to-head” and “head-to-head” are shown in Figure 23.

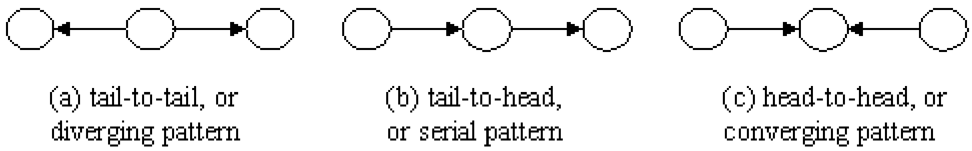


Figure 23: d-separation- Patterns for paths through a node

6.2 Insights from Literature

Structure of the BN built reflects two concepts from literature in PSS which are:

- The match between supply and demand (Sasser, 1976)
- Availability contract as an instance of PSS requires alignment of different stakeholder goals through incentives to meet the customer-oriented key performance indicators (Kapletia and Probert, 2010).

The first concept refers to the match between supply and demand in service. This came as a breakthrough in 1976, when Sasser (1976) article “Match supply and demand in service industries” was published in Harvard Business Review. Sasser (1976) state that balancing supply and demand in service industry is not simple and whether the service manager is able to do it well or not is all the difference it makes. Hence, this concept proposed by Sasser (1976) is applied while structuring the BN. The BN consists of variables related to supply such as availability of spares, availability of personnel, availability of work bench etc. on one hand and variables related to demand such as service demand, performance metrics to be met by stakeholders such as turnaround time, equipment readiness and maintenance personnel efficiency required to meet service demand effectively. The balance between supply and demand variables is significant. Match between supply and demand is said to influence quality of the service and resource productivity targets (Armistead and Clark, 1991). BN can be used in optimisation (Vans, 1998; Parakhine et.al. 2007) and here the inclusion of the above concept would enable in optimisation of supply and demand variables in order to achieve the required performance metrics.

The second concept is the alignment of different stakeholder goals through incentives to meet the customer-oriented key performance indicators is significant when manufacturers are moving from product to solution (Kapletia and Probert, 2010). Supply chain optimisation is determined by how a set of performance metrics is achieved (Beamon, 1998). There is a need to minimise loss generated because of conflicting goals in supply chains by matching the performance metric of individual supply chain with those of the entire supply chain (Lee and Whang, 1999). In the industrial scenario implemented using BN, OEM is striving to achieve equipment readiness as the performance metric at the system level. The level 1 supplier is required to address a different performance metric at the sub-system/component level, such as turnaround time. An alignment of these two performance metrics, is essential for successful execution of availability contract in the industrial scenario adopted in this research.

As discussed earlier, the two basic steps involved in establishing the structure of a BN are identification of uncertain variables that are relevant and determination of how those uncertainties are causally or influentially related to each other (Lucas et.al. 2013). Identification of the uncertainties relevant to industrial scenario was presented in Chapter 4. The uncertainties identified are characterised using the multi-layer uncertainty classification (see Chapter 5), which further shed light on the uncertainty characteristics they exhibit. In the subsequent Section, the process followed to determine the relation between these uncertainties is described, which is the second step towards establishing the structure of BN.

6.2.1 Identification of Relation between Uncertainties

The relation between some uncertainties enlisted is determined by a process based on literature mining. Literature mining is a popular application area for text mining where a large collection of literature (articles, abstracts, book excerpts, and commentaries) in a specific area is processed using semi-automated methods in order to discover novel patterns (Turban et.al. 2007). Literature mining methods are of two types, which are bottom-up (pairwise) and top-down (domain model based) methods (Antal et.al. 2004). Where, the former method identifies individual relationships and the integration is left to the domain expert while the latter, focuses on identifying consistent domain models.

The approach used in this research is based on bottom-up or pairwise method of literature mining, however it is manually performed to a large extent with the use of widely available tools such as google search engine and the adobe search function. The individual uncertainty dependencies are identified from literature by adopting the steps proposed by Mathiak and Eckstein (2004) and these dependency relations between uncertainties is integrated by the author to form sub-networks of the BN. The following steps were carried out for identifying relation between uncertainties (adopted from Mathiak and Eckstein, 2004):

1) **Literature gathering**

The method used for identifying the relation between uncertainties relevant to the industrial scenario is through an extensive targeted literature search and analysis. The literature contained journal articles, conference proceedings, thesis, books, and various defence reports. Examples of articles include journals such as International Journal of Operations and Production Management, International Journal of Service Industry Management, Journal of Service Management and CIRP and databases such as emerald, EBSCO, IEEE explore, Science direct, Scopus, Springer etc. The initial keywords were product service systems, maintenance management, performance-based contracts, supply chain, service, performance metrics and life cycle costing.

2) **Literature pre-processing**

The numerous journal articles, conference proceedings etc. were organised into appropriate folders, based on the theme of the paper identified from the abstract. The common themes identified are supply chain, performance-based contracting, organisation factor in PSS, product element of PSS and service element of PSS. This segregation of literature would ease the analysis step, by providing the author an indication to the kind of keywords to be used for searching the individual documents in the next step.

3) **Literature Analysis**

This step involved manual annotation of the documents with different pairs of keywords. The selection of pairs of keywords, represented the uncertainties which were presumed to be influentially or causally related were marked-up. Choice of the pairs of keywords used was made looking at the uncertainties considered as relevant to the industrial scenario to be modelled using BN. This method of tagging documents with pairs of keywords, enabled to perform co-occurrence analysis, which quantifies the pairwise relation of uncertainties by their relative frequency (Stapley and Benoit, 2000; Jenssen et al., 2001). However, some dependencies were widely reported in literature e.g. availability of spares and failure rate. On the other hand, some relations were not immediately apparent. After reading and understanding the relevant context or scenario presented in literature, the uncertainties being related becomes evident. The Adobe search function was used for searching pairs of relations between uncertainties in pdf files. The search function allows users to scan the document, in its entirety or by section, for specific words or phrases. The structure of BN which requires identification of relation between uncertainties is derived and justified from co-occurrence counts (Goebel and Gruenwald, 1999; Maskery et.al. 2008). Hence, in this step co-occurrence analysis is conducted, which quantifies the pairwise relations of uncertainties by the relative frequency of their occurrence in literature (Stapley and Benoit, 2000; Jenssen et al. 2001).

4) Visualisation

This step intends to present results of the co-occurrence analysis in a legible and clear manner. The simplest is just to make a table for the user to look up the information that is needed (Mathiak and Eckstein, 2004). Representing the results of co-occurrence analysis in a table format, with an indication of the frequency of their occurrences in literature induces transparency in to the process. This is presented in Table 10. A look-up table with pairs of uncertainties found to have an influential or causal relation and their frequencies of occurrence in literature will allow clear choices while establishing the structure of BN. 10 relation between uncertainties were identified from literature.

Table 10: Identification of Relation between Uncertainties using Co–occurrence Analysis

Influencing factor/ Cause	Influenced factor/ Effect	Frequency	Reference
Service Demand	Availability of spares (OEM facility)	4	Cohen and Lee (1990); Aurich et.al. (2006); Kennedy et.al. (2002); Dekker (1998)
No Fault Found	Availability of spares	2	Hockley and Phillips (2012); Warrington et.al. (2002)
Requisition Wait Time	Availability of spares	1	Owens et.al. (2006)
Safety Stock	Availability of spares	3	Kennedy et.al. (2002); Roy and Cheruvu (2009); Huiskonen(2001)
Production Lead Time	Safety Stock	2	Liao and Shyu(1993); Eppen and Martin (1988)
Service Demand	Availability of personnel	2	Colosi et.al.(2010); Mjema (2002); Thorsteinsson(1995)

Availability of spares	Turnaround time	2	Barabady and Kumar(2007); Qingwei et.al.(2011)
Equipment usage	Failure rate	2	Endrenyi et.al. (2001); Peltz (2004)
Remaining useful life (RUL)	Failure rate	2	Peltz (2004) Finkelstein(2008)
Availability of spares	Equipment readiness	1	Peltz (2004)

6.3 Insights from Industry

Insights from industry are drawn from four working meetings and other various opportunities for discussion with industry personnel. The working meetings took place at the OEM and their level 1 supplier facilities and Steering meetings, which took place at interval of 2 to 4 months, since 2011. Steering meetings were attended by three industry contact personnel representing the customer, OEM and the level 1 supplier and all the academics and researchers of the CATA team. Initially all the researchers in the CATA team, proposed a representation of the activities by their choice of method. The author used cross functional flow chart to represent the activities, which was used to analyse the industrial scenario adopted in this research and identify the relevant variables, as discussed in Chapter 4. Researchers at University of Bath developed IDEFO maps to represent all the activities in regard to delivering availability of MHDD. In order to identify the relation between uncertainties, the IDEFO developed by Thenent (2013) and the cross functional chart was used to identify the uncertainties relevant to the case study.

The different activities involved in delivering MHDD availability relates to MHDD repair, cost control, aircraft availability provision and on-base activities (Thenent, 2013). Level 1 supplier performs MHDD repair and OEM is responsible for ensuring equipment readiness for the mission at hand. The industrial scenario adopted in this research focuses on MHDD repair and hence IDEFO maps related to MHDD repair and handling are presented in Figures 24 and 25 below. The IDEFO maps developed by Thenent (2013) emphasises on information flow. Here the focus is on the activities represented by the IDEFO maps and hence the labels pertaining to information flow is not considered.

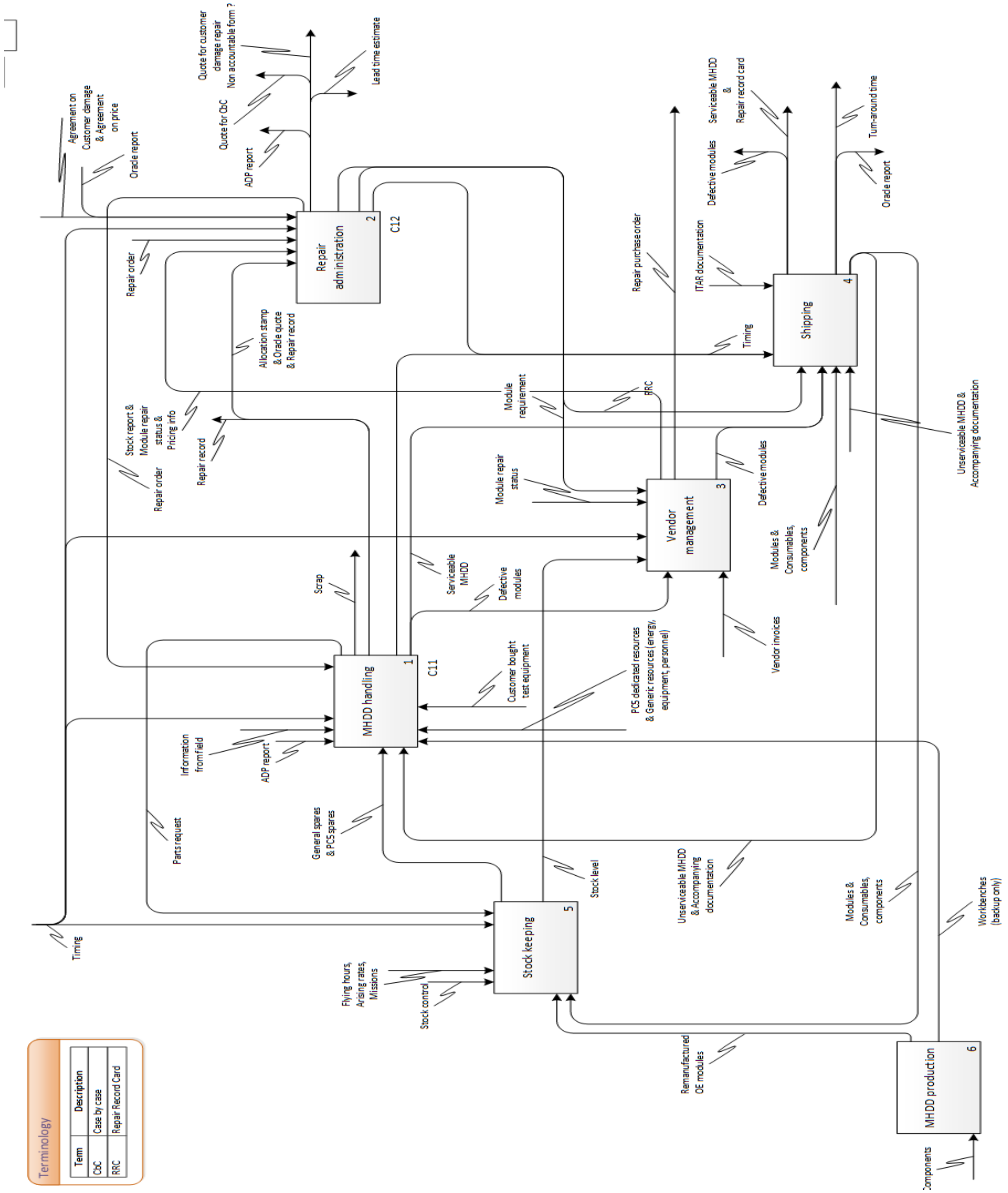


Figure 24 : IDEFO Representation - MHDD Repair (Thenent, 2013)

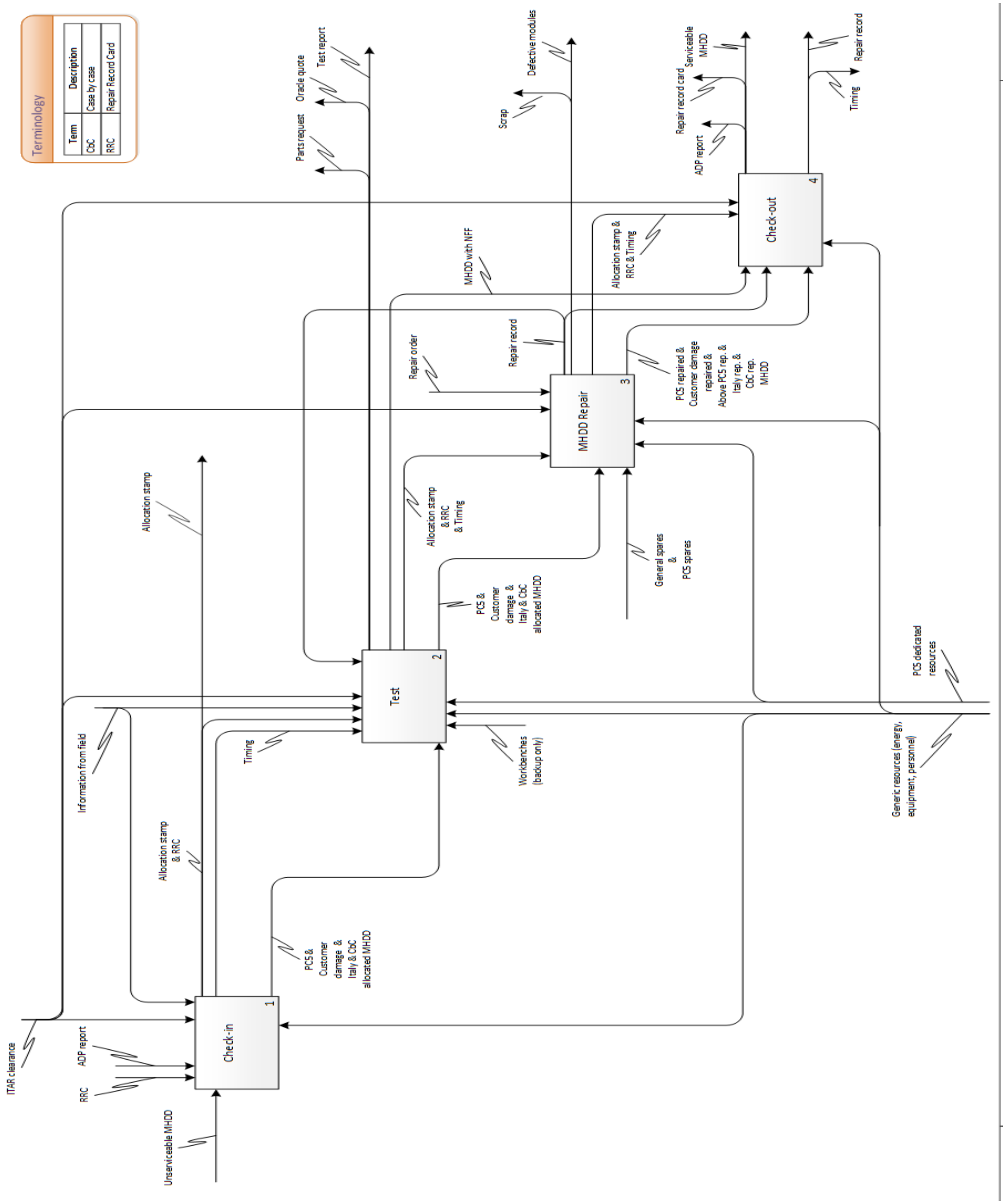


Figure 25: IDEFO Representation - MHDD Handling (Thenent, 2013)

A three day industrial visit (17th to 19th April 2012) was conducted to understand the process involved in providing MHDD to customer under the arrangement of availability contracts. This visit included key stakeholders in availability contracts for MHDD. OEM and their prime level 1 supplier facilities were visited. During the visit, there was interaction with personnel's working in the shop floor of hanger, managers and programme director. This visit highlighted many exclusive facts relevant to availability contracts, including the obstacles that can increase repair time indirectly if not directly such as confidentiality induced by the contracts, intellectual property, degree of sub-contracting etc. The information gained during this visit transitioned to knowledge, which enabled the author to see dependencies between uncertainties identified. The 22 relation between uncertainties informed primarily from industry are presented in Table 11 below.

Table 11: Identification of Relation between Uncertainties from Industry

Influencing factor/ Cause	Influenced factor/ Effect
Availability of personnel	Turnaround time
Availability of test equipment	Availability of work bench
Availability of work bench	Turnaround time
Customer damage	Failure rate
Degree of contracting	Supply chain visibility
Failure rate	Service demand
Infrastructural capability	Service demand
Level of confidentiality	Supply chain visibility
Level of skill & knowledge	Availability of personnel
Level of skill & knowledge	Service personnel efficiency
Service personnel efficiency	Turnaround time
Operating environment	Failure rate
Quality of support	Supply chain visibility
Intellectual property	Service demand

Retrograde duration	Service demand
Service demand	Availability of work bench
Supply chain visibility	Requisition wait time
Task complexity	Availability of personnel
Task complexity	Service personnel efficiency
Transport time	Availability of spares
Turnaround time	Availability of spares
Demand for contractor/in-house spares	Availability of spares

The manner in which these relationship between uncertainties was identified is addressed in the next section. It discusses merging of findings from literature and industry by mapping the uncertainties to the IDEFO maps developed by Thenent (2013).

6.4 Merging of Findings from literature and industry

The insights from literature and industry were integrated and captured to synthesise the BN structure. This section discusses forming of sub-networks of the BN. 12 sub-networks constituted the BN structure, where the IDEFO maps were transformed to BN by mapping clusters of uncertainties to each activity represented in the IDEFO. *IDEF*O (Integrated Definition for Function Modelling) is a graphical modelling methodology developed for modelling activities and information flows in systems. Thenent (2013) developed IDEFO maps presented above to capture information flow, for example documents, reports etc. and the main activities were captured implicitly which is innate to IDEFO representation. As our focus is on the uncertainties arising in these activities, the various uncertainties were tagged to the activities represented in IDEFO, as shown below. Khoo et.al. (1999) have used IDEFO for diagnosing manufacturing system, which was translated to digraphs or directed graphs. Bayesian Networks is an example of modified diagraphs, where direction of the arcs are characterised to be acyclic. They used IDEFO to facilitate stepwise revelation of the system using hierarchical decomposition. This orderly break down of a complex system into its constituent parts allowed IDEFO representation to be transformed to diagraphs (Khoo et.al. 1999). The mapping of uncertainties to IDEFO is transformed to BN in three steps, as follows,

- IDEFO unveiled all the activities and sub-activities performed to deliver MHDD availability. The various uncertainties relevant to the industrial scenario, which were identified in Chapter 4 are mapped to the various activities represented in IDEFO map.
- The clusters of uncertainties identified for each activity is analysed for pairs of uncertainties having influential or causal relation.
- These are arranged and structured into Directed Acyclic Graphs (DAG). The arrangement of pairs of uncertainties having relationship into sub-networks of the BN is guided by the two theoretical concepts discussed earlier in Section 6.2. The first concept was match between demand and supply and the second concept was alignment of performance metrics of different stakeholders. Figure 30 shows the BN structure obtained from this process, which reflects the above two concepts. Before that, Figures 26 and 27 present mapping of uncertainties to IDEFO maps in order to be transformed to DAG.

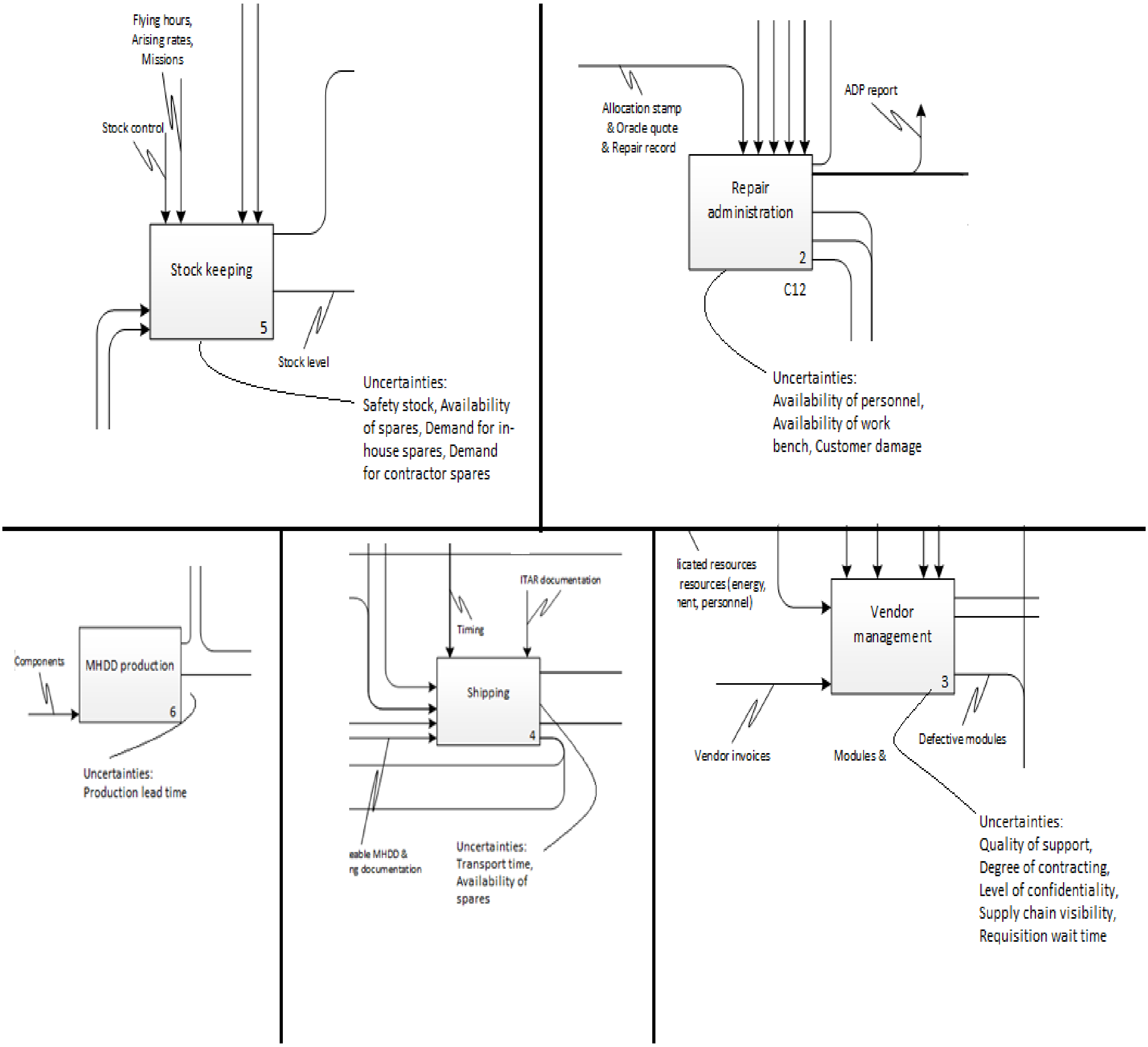


Figure 26: Mapping of Uncertainties to MHDD Repair Activity

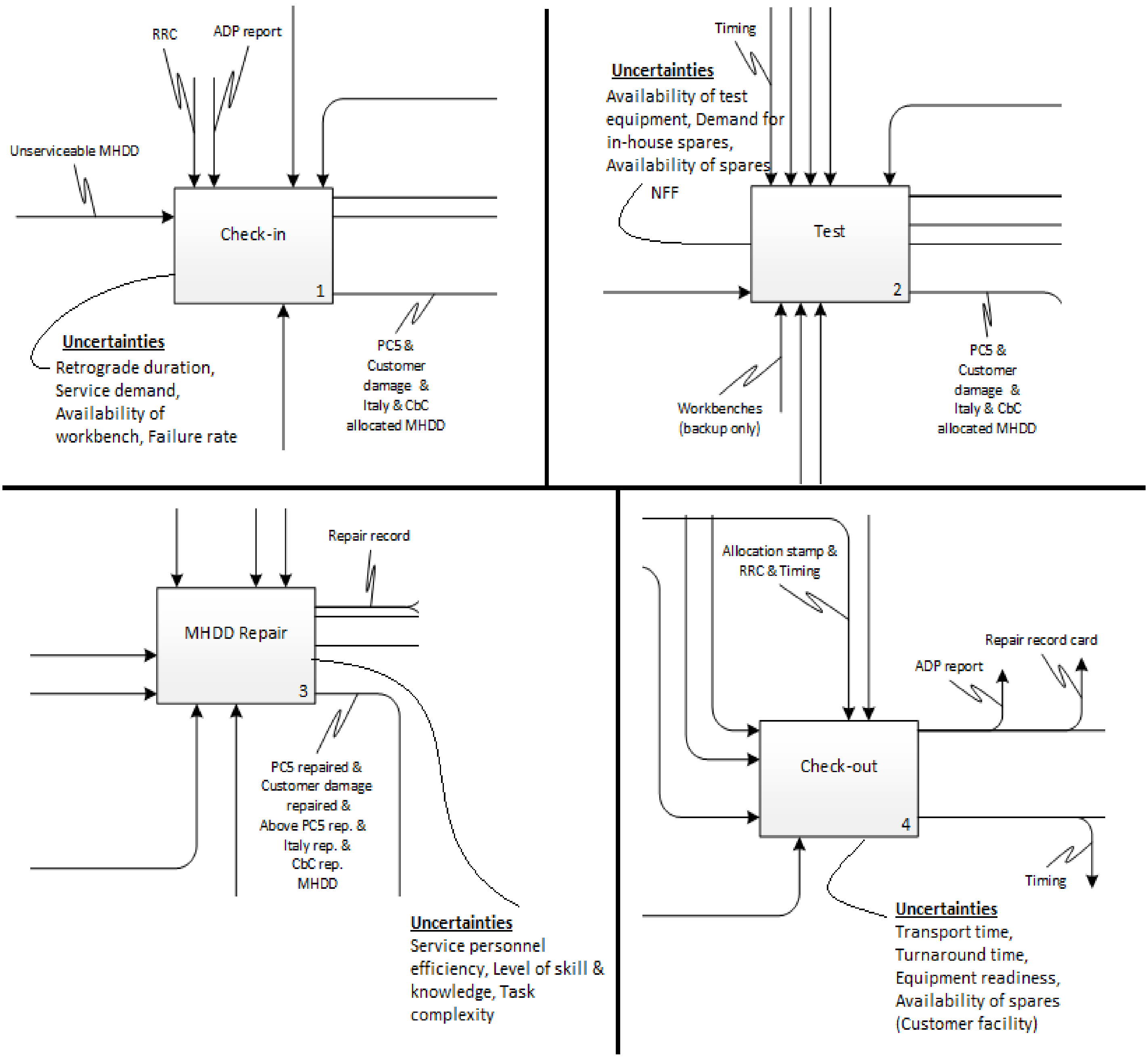


Figure 27: Mapping of Uncertainties to MHDD Handling Activity

12 sub-networks were formed, where each had different number of parents and types of uncertainties, such as discrete and continuous. Eight sub-networks were identified, where the child node had at least two and a maximum of seven parent nodes. There were four sub-networks where the child node had only one parent node. Therefore, in total 12 sub-networks form the BN structure.

6.5 Validation of Bayesian Network Structures

Validation is defined as the ability of a model to depict the system that it is intended to describe both in the output and in the mechanism by which that output is obtained (Pitchforth, and Mengersen, 2012).Validity is often discussed in terms checking the internal consistency of BN structure, which is statistically valid. Commonly discussed methods for obtaining a statistically valid structure are d-separation analysis and causal independence-based tests (Pitchforth, and Mengersen, 2012). Literature on systematic validation of BNs by experts was very sparse. However, a significant piece of research done by Pitchforth, and Mengersen (2012) present systematic validation of BN using experts. They present a validity framework consisting of seven validity methods such as nomological validity, face validity, content validity, concurrent validity, convergent validity, discriminant validity and predictive validity. Some sample questions framed under each method was also presented and it was found that some of the questions would be quiet difficult for the expert to answer in the authors view. It requires expert to have extended knowledge to be able to analyse the output derived from compilation of BNs, familiarity with the software's used for compiling BNs and interpretation of visual graphics of BNs on the software user-interface. In this research, not all the seven methods would be implemented because there is no reference or base model required for other tests. In Pitchforth, and Mengersen (2012), some tests made an assumption on the existence of a latent, unobservable 'true' model (or set of acceptable 'true' models) for the phenomenon of interest against which the expert elicited model can be compared. Hence, only face validity test related to structure of BNs is carried out in this research. Face validity is one of the most commonly used tests, however it is affected by criterion contamination issue that arises when the test dataset is the same as the validation set (Pitchforth, and Mengersen, 2012). But this is overcome here, because the BN structure is derived by the author and validity test is assessed by industry personnel, hence there is split into experts who form the validation group and the author, who has used insights from literature and industry to formulate the BN structure.

This captures whether industry personnel think the network looks the same as expected and agree with the structure presented. Apart from using likert scale, questions (Pitchforth, and Mengersen, 2012) were posed to experts to validate the BN structure, which are presented below.

- Does the model structure (the number of uncertainties, uncertainty labels and arcs between them) look the same as you and/or literature predict?

- Is each uncertainty of the network discretised/separated into sets that reflect your knowledge? For eg. all uncertainties with discrete values such as *Supply chain visibility* has high, medium & low values; *Service personnel efficiency* has high, low & medium values. Do these descriptors suffice, if not please provide alternatives.

The experts gave positive feedback for the above questions. One expert stated the following about model structure.

"Based on my knowledge of the supply chain and maintenance activities the model appears to be an accurate reflection of how I see turnaround time being driven".

In regard to states of the uncertainties in the BN structure, the expert quoted this.

"I think the network variables are properly balanced".

A more quantitative edge to validation was given by the usage of likert scale. Likert scale method is a psychometric scale commonly involved in research that employs questionnaires. The format of the five-level likert scale used is,

1. Strongly disagree
2. Disagree
3. Neither agree nor disagree
4. Agree
5. Strongly agree

Any comment or feedback for improving the model structure was also sought. The industry contact personnel largely agreed with the model structure, however further to the feedback and response received, BN underwent slight refinements. The validation document, which was forwarded to the industry personnel, is presented in Appendix B.

There was general agreeability on the different uncertainty relations presented in the BN. 55.32% of uncertainty relations were scored with strongly agree. Figures 28 shows the individual response pattern of the three industry contact personnel and Figure 29 shows pie chart drawn from the likert scale scoring.

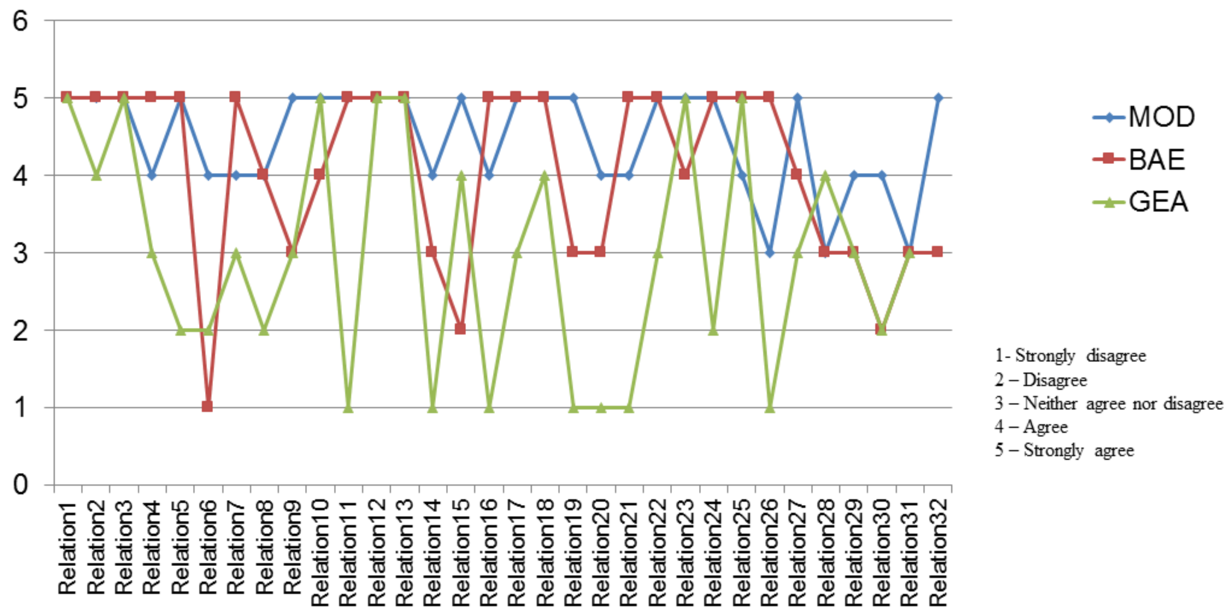


Figure 28 : Response Pattern of the Three Industry Contact Personnel

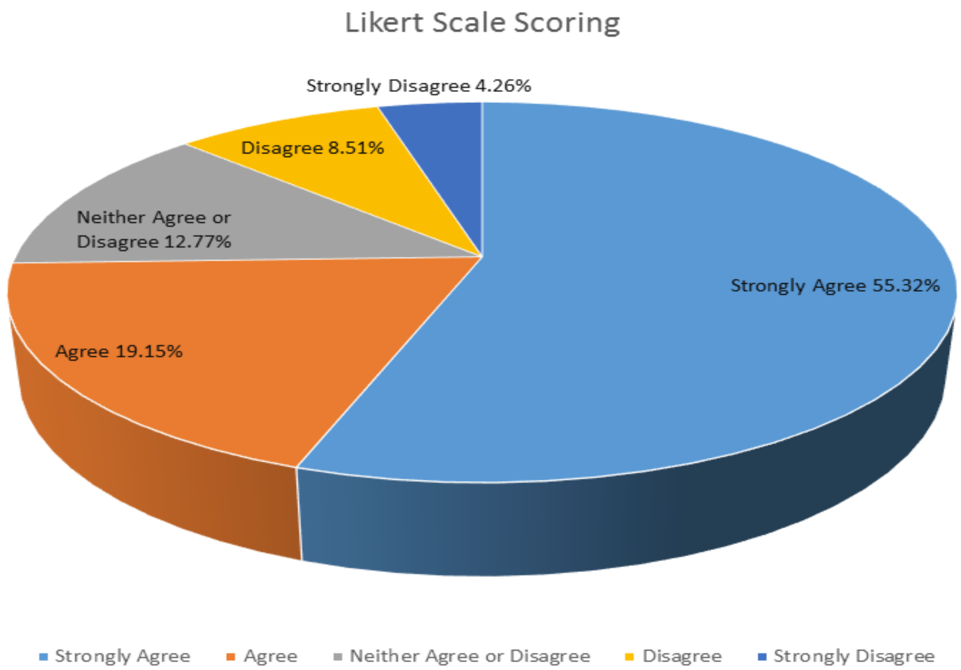


Figure 29: Validation using Likert Scale Scoring

Based on the likert scale scoring and feedback received during the validation, refinement of BN was carried out. Some uncertainty relations were removed because of weak scoring For example: *Technological change* and *Turnaround Time*; *Back orders* and *Turnaround Time*. It was perceived by industry personnel that MHDD was in a settled phase as a legacy product, with no predictable technological change arising. Node Fill rate was removed as it was semantically very close to availability. The node *Operational readiness* was replaced with *Equipment readiness*. The former was usually related to the whole aircraft, and in order to focus the BN model to the exemplar product used in the case study, which is MHDD, *Equipment readiness* was seen as more appropriate. The following section presents the assumptions which underpin the BN structure and some relate to the uncertainty characteristic of the nodes. These assumptions do not affect the quality of the model, they are made to incorporate lack of data and facilitate initial modelling which could be subject to iterations of refinement in future work.

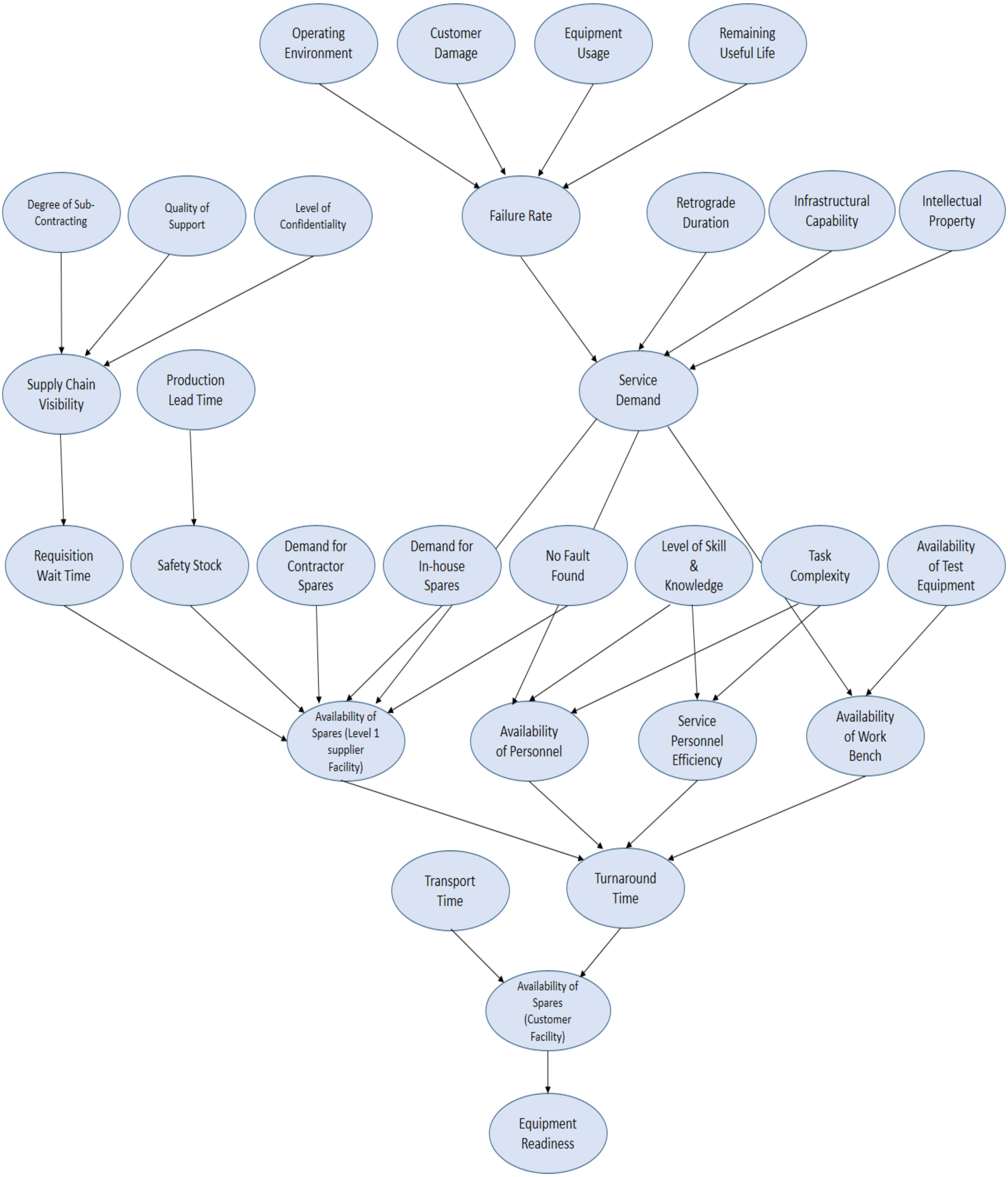


Figure 30: Bayesian Network Structure

6.6 Assumptions on Bayesian Network

The BNs proposed in this research attempts to understand the degree to which the performance metric of the OEM and level 1 supplier are in tune or not with each other. To simplify and present a manageable BN, some assumptions were incorporated. The assumptions do not place any significant limitation on the simulation as it represents a general process involved in delivering equipment availability. Lack of data, time constraints and availability of experts have been the primary reasons for adopting these assumptions. The following assumptions were made, based on which the BN were constructed and compiled.

- Some spares were manufactured in-house while others were outsourced to a contractor as in the industry case study. Spares is a module of MHDD that is replaceable if found faulty. The some in-house spares were assumed to be buffered as safety stock, which is readily available on shelf.

- Requisition wait time is associated to the contractor supplied spares. It is assumed that no contractor-supplied spares were inventoried by the level 1 supplier. Hence, it is assumed that just-in time inventory was implemented for contractor-supplied spares when the demand arises.

- MHDD’s are legacy products, which have reliability predictable to an acceptable level. Level 1 supplier do not manufacture new spares currently. Hence, they do not have production lead time influence on MHDD readiness. However, if new in-house spares are being manufactured, it will also influence the level of safety stock held. It is assumed here, that production lead time influences the availability of in-house manufactured spares.

- MHDD’s are repaired only at the level 1 supplier facility. There is no infrastructure to support restoration of MHDD’s at the customer facility. However, it was assumed that the minimal infrastructural capability in terms of tools, consumables etc. are available at the customer site and may vary from low to high. The node infrastructural capability is assumed to be a discrete node, with values low, medium and high. As the linguistic descriptors imply, low could be interpreted as availability of minimal diagnostic capability, trained personnel and tools to repair. Medium could be slightly advanced availability of diagnostic capability etc. to restore unserviceable MHDD and high is the complete availability of diagnostic capability etc. with more ability to restore unserviceable MHDD at the customer site.

- OEM is an intermediary link between customer and level 1 supplier. To simplify, some OEM activities are not considered in providing MHDD readiness. For example, it was identified that an inventory of MHDD is maintained by OEM at their facility and MHDD navigates from customer to OEM then to level 1 supplier. In this research, it is assumed MHDD is shipped directly between customer and level 1 supplier.

- It was assumed that an inventory of spares is maintained at the customer site, which is replenished regularly by level 1 supplier. In real, an inventory of MHDD is maintained at the OEM facility. This assumption would not affect the level of inventory to be maintained, which is vital. However, the location of inventory and the navigation route of the MHDD may affect transport time. This effect on modelling results could be dealt, by entering for a higher transport time in findings field, while compiling the BNs and could simulate for a higher transport time.

- It was assumed that the OEM works towards the performance metric *Equipment readiness*. In actual, ensuring availability of a fleet of aircrafts is the OEM's goal. However, to simplify it was focussed on MHDD only and not the whole aircraft. Hence, *Equipment readiness* refers to MHDD readiness capable of achieving the required mission.

- In regard to the characteristics of uncertainties modelled in the BN, some assumptions have been placed. All uncertainties are considered epistemic. All have manifest effect. Suggestion from source characterisation has not been completely taken into consideration to due limited resources in terms of experts availability, time etc. The interviewees were in job profiles ranging from director level to shop floor technician and they were all involved in activities affecting the delivery of MHDD availability to customer. The nodes which are categorised as epistemic can be targeted in further iterations of BN modelling to elicit additional information from experts especially if they rank high in sensitivity analysis. However, in the application of this characterisation to the Industry case study, all the uncertainties are assumed epistemic and hence PDF of all the uncertainties is elicited from experts, which is discussed in detail in Chapter 7.

6.7 Conclusion and Summary

This chapter presents the steps involved in determining the structure of BN. Insights from literature as well as industry is integrated to derive the various uncertainty dependencies. These uncertainty dependencies are organised together to form the structure of BN. The structure of BN reflect two underlying concepts. Firstly the match between supply and demand and secondly the alignment of performance metrics of different stakeholders. Various approaches to derive BN structure have been proposed, which include expert knowledge, data, literature etc. However, use of expert knowledge and literature to formulate BN structure was not found in literature. The information from literature was analysed in four steps motivated from text mining domain area. The four steps carried out include literature gathering, literature pre-processing, literature analysis and visualisation. The insights from industry was obtained at different occasions, which include industry visits, steering meetings and working meetings. An initial validation called face validity of the BN structure was conducted using likert scale scoring. Assumptions were formulated to neutralise the effects of information and data paucity and modelling flexibility. This chapter renders novelty in terms of the approach adopted for deriving the BN structure, which is the integration of insights from literature and industry. Research using this approach was not found in literature. Theoretical concepts such as, match between supply and demand and alignment of performance metrics of different stakeholders, which the BN structure reflect is unique and enforces the application of BN to concept-oriented modelling rather than mundane cause-effect modelling. Some uncertainty relations, for example relation between *Intellectual property* and *Supply chain visibility*, identified are novel to the case study of this research. Here the BN structure brings service provision aspect of availability contracts to the forefront. It emphasises factors which the PSS provider has to consider unlike in manufacturing due to characteristics of service such as its inability to be inventoried, high degree of interaction between service provider and customer, non-portability of service and the intangible nature of service output.

7 Elicitation of Expert Judgements for Probabilistic and Dependency Information

Bayesian networks consist of both qualitative and quantitative constituents (Renooij, 2001). The qualitative part includes the uncertainties and arcs which forms the Directed Acyclic Graph (DAG), as presented in Chapter 6. The uncertainties are modelled as nodes and the arcs as probabilistic influences. The quantitative part includes the probabilities encoded over these uncertainties (Druzdzel and Van der Gaag, 1995). The probabilities required are prior probabilities for all uncertainties with no parents and Conditional Probabilities (CP) for all uncertainties with parents. This large number of probabilities required is a major hindrance in the construction of BNs (Renooij, 200; 1 Druzdzel and Van der Gaag, 1995). Probability elicitation can be defined as a formal process of extracting probability estimates in a way to reduce bias and overconfidence (Dalton et.al. 2012).

The focus of this chapter is to present the elicitation protocol and the methods adopted for eliciting prior and Conditional Probabilities (CP). When this information is input into the software used for BN modelling, we would obtain useful results as discussed in the subsequent chapter. Section 7.1 presents segregation of uncertainties into discrete or continuous type. The decision related to this modelling aspect is supported by the multi-layer uncertainty classification presented in Chapter 5. Section 7.2 addresses the elicitation protocol adopted in this research for obtaining information regarding prior probability distribution using quartile method. Section 7.3 presents rank correlation method and likelihood method which are used to populate CPTs in the BN. The subsequent section presents summary and conclusion for the chapter. Appendix E contains the questionnaire pack designed for the elicitation procedure.

7.1 Continuous and Discrete Uncertainties

Extant background of theory and methods have been developed for cases, where all the variables are discrete. However situations in which continuous and discrete variables appearing in the same problem are common in practice (Cobb et.al. 2007). BNs where both discrete and continuous variables appear simultaneously are called *hybrid Bayesian Network* (Cobb et.al. 2007). The uncertainties in the BN structure built can be specified as continuous or discrete based on its characteristics. By specifying the scale level characteristic of the uncertainty classification, one can categorise them as discrete or continuous. It should be noted that some uncertainties can be expressed on both numerical and linguistic scale level. For example, service personnel efficiency could be expressed by a numerical score of the duration taken by the personnel to complete a repair. It can also be expressed linguistically as high, medium or low. However, here it is assigned the scale taking into consideration availability of data, experts easy for probability encoding etc. Continuous and discrete uncertainties require different approaches for elicitation of prior probability distribution and dependency elicitation methods. Prior probability distribution for continuous uncertainties is realised using quartile method, whereas direct probabilities are elicited for different states of discrete uncertainties. In regard to dependency information elicitation, rank correlation method is used for sub-networks of the BN that contain continuous uncertainties as well as sub-networks containing a mix of continuous and discrete uncertainties. Likelihood method is employed to elicit dependency for sub-networks in the BN containing only discrete uncertainties. These are discussed in the subsequent sections.

7.2 Elicitation of Prior Probability Distribution using Quartile Method

The SRI/Stanford protocol (Spetzler and Stael Von Holstein, 1975 and Stael Von Holstein and Matheson, 1979) is adopted as the structured protocol to follow whilst eliciting prior probability distribution using quartile method.

Amongst all the protocols for expert assessment described in literature, Stanford or SRI interview process developed by a group of decision analysts in the department of engineering-economic systems at Stanford University and at the Stanford Research Institute during the 1960s and 1970s is the most influential (Morgan and Henrion, 1990). Morgan and Henrion (1990) identify the Stanford Research Institute (SRI) assessment protocol as, historically, the most influential in shaping structured probability elicitation. Kind of information sought, time constraints and uses that will be made of the data are factors that influence the choice of an elicitation procedure (Burgman, 2006). The simplistic five stages of the SRI protocol was suitable within the constraints of expert time and for eliciting prior probabilities in this research. It is designed around a single expert (subject) and single elicitator engaged in a five-stage process. A similar scenario persists in this research, where author is the only elicitator and industry personnel are interviewed one at a time. SRI protocol does not emphasise on providing any additional study or data acquisition, in terms of training (Hora, 2007). As the industry personnel have worked on different areas of the Typhoon project such as logistics, reliability, inventory management etc. and had experience of 2 to 10 years in their job role with sufficient knowledge on probability theory and hence, training was not considered necessary. However, some material on basics of probability theory was provided to refresh their memory prior to the interview. SRI technique suggests using face-to-face interaction between the elicitator and the expert rather than having a subject fill out a questionnaire or using interactive computer interview (Spetzler and Von Holstein, 1975). This allows the elicitator to observe any biases the expert may have and provides opportunity to overcome and provide any explanations as required. Hence, the wide popularity of SRI protocol, its design for single expert-single elicitator and face-to-face interview setting and flexibility on additional expert training were reasons for employing SRI protocol in this research. The initial SRI protocol was summarized in Spetzler and Von Holstein (1975), however over the years researchers have suggested variations of the original SRI protocol (Merkhofer, 1975). The version of the SRI protocol employed in this research uses indirect fixed-probability method for encoding probabilities (Merkhofer, 1975).

Questions for prior probability distributions in this research were primarily framed using relative-frequency type questions. Relative-frequency type questions have been found to reduce random response error in experts likelihood judgements, less scatter, whilst encouraging the use of likelihood judgements, implements simpler algorithms and have greater internal consistency than does a direct probability question (Price, 1998). A web-based tool is used to facilitate elicitation of quartiles and software application is said to enhance efficiency of elicitation (Dalton et.al. 2012).

SRI Protocol

The SRI protocol consists of five steps, which includes motivating, structuring, conditioning, encoding and verifying (Spetzler and Stael Von Holstein, 1975 and Merkhofer, 1975). These steps are discussed below:

1) Motivating - In this step, rapport with the expert is developed and any conscious or sub-conscious biases prevailing in experts mind towards the uncertainties or project is explored. While carrying out the elicitation, it was observed that the experts did not have any bias towards any specific uncertainty. However, they were initially biased towards the organisation they represented, especially when assessing uncertainties related to performance such as maintenance personnel efficiency etc. It was overcome by explaining one of the purpose of BN, was to capture the most adverse state of uncertainties and encouraged the experts to think of values at worst case scenarios as well.

It was observed that experts were hesitant about the accuracy of their assessments. As such, they were ready to provide values for quantitative variables which they were aware of, whereas the qualitative variables seemed more demanding in terms of accuracy for them. They were not sure about the level of accuracy in their estimates. This was overcome by explaining them that any uncertainty in their estimates will be dealt with, by being represented as a probability distribution and their estimates may have considerable uncertainty about some of these variables (though less than that of a lay person). This will not be of concern during the elicitation itself, as the outputs from the elicitation will reflect large uncertainty when it is present (Oakley and O'Hagan, 2010).

2) Structuring - In this step, the uncertainties were defined and clearly structured. Structuring was partly achieved during the validation of the BN structure, where all the uncertainties constituting the BN was agreeable and understandable to the expert. The uncertainties were subject to Clairvoyant test, to ensure that their definitions were unambiguous and clear. A scale of measurement is chosen for each of the uncertainties in the BN. Continuous variables, such as failure rate was measured in units per month, whereas discrete variables such as supply chain visibility were given descriptive labels such as high, medium and low, to describe their measurement qualitatively.

During structuring, the experts were also initiated to think about uncertainties and scenario of the problem. Whilst exploring the experts opinion about the problem, any background information that might be relevant (or irrelevant) to the problem was discussed. This was conducted by forwarding questionnaire to be used in the face to face elicitation process before hand to the experts. The questionnaire, had all the information regarding the elicitation process and it initiated them to think about uncertainties and the scenario on which the BN were based on. Since all the experts were engaged in availability contracts, they were familiar with the concepts presented in the BN. They also acknowledged the structure of the BN, which was discussed in detail in Chapter 8. Some experts were not familiar with some uncertainty names, for example, Supply chain visibility, however once the definition was explained, they subscribed to the idea and could relate to their job profile. In this case, they understood supply chain visibility as information access.

3) Conditioning – The manner in which the expert provides estimates can unfold information on availability, experts biases towards any uncertainty and implicit use of unstated assumptions was observed. When the experts were queried about the bases on which they are were providing estimates, it was usually based on previous years results or data and this could cause central bias. This was overcome by eliciting the extreme values first and then the median value (O'Hagan et.al. 2006). For quantitative variables, the experts had ideas about plausible values, due to them working on databases such as *Failure Reporting, Analysis and Corrective Action System (*FRACAS).. FRACAS is typically used in an industrial environment to collect data, record and analyse system failures. Experts were asked to visualise scenarios that would produce extreme outcomes in terms of best and worst case scenarios and further scenarios that might lead to outcomes outside of those extremes were queried in order to obtain upper and lower values for the uncertainties. The order of querying used was median, upper value and then the lower value minimises the effect of anchoring and adjustment. An effective approach to neutralise anchoring and availability bias the author elicited extreme values of the uncertainty and then asked the expert to describe scenarios that would explain these outcomes. For example, while eliciting estimates for turnaround time, the experts explained that an extreme value of 60 days occurs, when *International Traffic in Arms Regulations* (ITAR) issues emerged. ITAR are regulations that control the export and import of defense-related articles and services on the United States Munitions List (Choi, and Niculescu, 2006). ITAR issues completely block any circulation of defence equipment.

4) Encoding – Both continuous and discrete variables were quantified using quartile method. Methods used for quantifying discrete and continuous variables are very similar because quantifying a continuous variable requires assessing the probabilities of discrete events based on the continuous variable (Merkhofer, 1975). Elicitation questions were slightly changed, when eliciting discrete variables. The upper and lower values of continuous variable are replaced with terms 'high' and 'low' descriptive labels for discrete variables. Median value for continuous variable as 'medium' value for the discrete variable. The questionnaire was designed using relative-frequency type questions. The experts were asked to visualise a population, for example 100 MHDDs (Multi-function Head Down Display) and give values they could typically observe within this population. Some sample questions asked to the expert and their response is presented below. The complete questionnaire can be found in Appendix E.

Q) Observing 100 random MHDD's operated by RAF, what is the plausible lower bound (L) and upper bound (U) values for remaining useful life at the current time?

Q) Observing 100 random unserviceable MHDD's shipped to customer from OEM, what is the plausible lower bound (L) and upper bound (U) values for transport time?

Q) Observing 1000 flying hours, what is the likelihood that a typical MHDD is exposed to combat and training operating environment?

Q) Can you determine a value, such that equipment usage is equally likely to be less than or greater than this point?

Q) Suppose you are told that equipment usage is below your assessed median. Can you now determine a new value (lower quartile) such that it is equally likely that equipment usage is less than or greater than this value?

Q) Suppose you are told that equipment usage is above your assessed median. Can you now determine a new value (upper quartile) such that it is equally likely that equipment usage is less than or greater than this value?

5) Verifying – In the last phase of the interview, the judgments are tested to see if the subject really believes them. If the subject is not comfortable with the final distribution, some of the earlier steps in the interview process were repeated. A graphical representation, in the form of PDF is shown to the experts, by fitting an appropriate probability distribution to the parameters elicited from experts. In this research, an online web-based probability distribution elicitation tool called MATCH uncertainty elicitation tool (Morris et.al. 2014) is used to perform the verifying step. Manually drawing the cumulative distribution function (CDF) was not feasible in terms of experts time. PDF is perceived by experts as a more intuitive graphical form (Merkhofer, 1975). Hence online web-based tool was used to fit the probability distributions for verifying the elicited probabilities. This tool is free to use and fits various parametric probability distributions to elicited parameters, using least squares procedure (Morris et.al. 2014). The tool enables the expert to visualise these judgements and adjust any values using the sliding bars in real time. In the verifying step check were performed on values elicited, for example, the expert may feel that the interval between 0.05 and 0.95 quantiles is a little narrow (Morris et.al. 2014) or PDF was checked for bimodal shapes or sharp extremes which should be discussed with the expert (Spetzler and Stael Von Holstein, 1975; Merkhofer, 1975). If these checks reveal any inconsistencies compared to experts belief, they are rectified to reflect the expert's belief.

7.3 Elicitation of Dependency Information

There are several methods proposed in literature for the elicitation of dependency between uncertainties, like direct elicitation of conditional probability, EBBN method, likelihood method, weighted sum method and rank correlation method (Ravinder et.al. 1988; Wisse et.al. 2008; Benedict, 2008; Das, 2004 and Hanea and Kurowicka, 2008). This section elaborates the methods adopted in this research for elicitation of dependency information between uncertainties, with the primary intent to populate the CPTs of all the child nodes in the BN. Dependencies between uncertainties have been elicited using two methods, which are rank correlation and likelihood method. Former method is used when most of the nodes involved in the sub-network are continuous uncertainties and some discrete nodes i.e. a hybrid BN, whereas the latter method is adopted when all the nodes involved were discrete uncertainties, which is discussed in subsequent sections.

7.3.1 Elicitation Using Rank Correlation Method

Rank correlation values are elicited directly from experts. An assumption is placed on the relationship between parents nodes in the BN. The parent nodes were considered independent of each other and only the individual influences of the parent nodes on the child node were considered. Each relationship between uncertainties could be assigned a value between -1 and 1. Some sample questions posed to the experts for elicitation of rank correlation values is presented below. The complete questionnaire pack for elicitation of prior distribution and dependency information as well as the rank correlation values elicited is presented in Appendix E.

Q) What would you estimate for the correlation ($r_{4,2}$) between Equipment Usage and MHDD failure rate (4)?

1strong positive *0 no dependence* *-1 strong negative*

Q) What would you estimate for the correlation ($r_{4,3}$) between Remaining useful life and MHDD failure rate (4)?

1strong positive *0 no dependence* *-1 strong negative*

The experts were given support material prior to the interviews, which contained scatterplots and verbal descriptors associated with different rank correlation values to enhance the experts understanding of it as shown in Figure 30. Rank correlation can take any values between +1 and -1. +1 indicates perfect positive correlation, which means when variable 1 increases variable 2 also increases. −1 indicates perfect negative correlation, which means when variable 1 increases, variable 2 decreases. A value of 0 indicates no correlation. The elicitation of rank correlation was supported by use of a scale which had both numerical and verbal anchors and this was used as rule of thumb for interpreting the correlation coefficient

After the rank correlation values are obtained representing association between uncertainties, this dependency information needs to be transformed to CPTs. Netica does not support population of CPTs using rank correlation values directly. Hence, a software called UNINET is used to generate CPTs, which are then exported to Netica. UNINET is a standalone program using BN designed by the Risk and Environmental Modelling group at the Department of Mathematics of the Delft University of Technology (Hanea et.al. 2006; Kurowicka and Cooke, 2006). This is explained in Chapter 9 under compiling BN using Netica.

7.3.2 Elicitation using Likelihood Method

Two sub-networks in the BN, which only have discrete nodes have their dependency information elicited using likelihood method. The two sub-networks are *Supply Chain Visibility* and *Service Personnel Efficiency* sub-networks.

In likelihood method, questions posed to the experts were suppose that you observe a particular value for the child node *'Supply chain visibility'* What probability would you assign to different combinations of the parent nodes? Hence more user-friendly elicitation questions are asked to the expert, like how much influence the different parent nodes might have on the possible outcomes of the child node. Bayes Table Generator is a tool used to derive CPTs using likelihood method. The generated CPT is exported into Netica software. The method as applied to the supply chain visibility sub-network is discussed below.

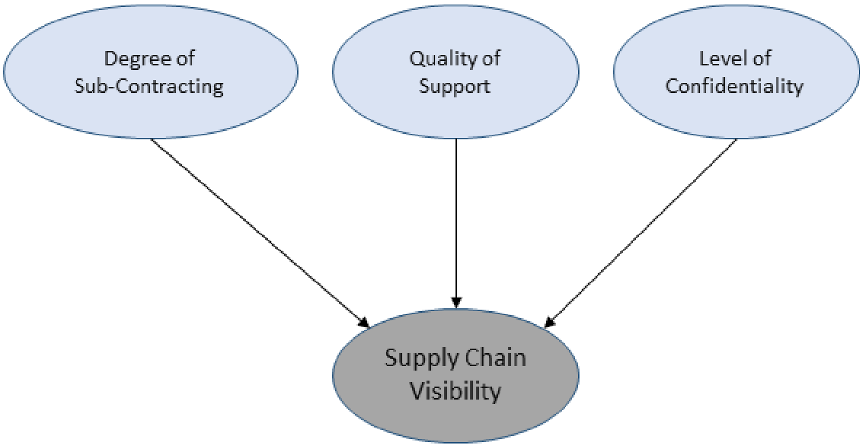


Figure 31: Supply Chain Visibility Sub-Network

Each node are given three possible levels: low (L), medium (M), and high (H). The initial distributions are assigned in the ratios L: M: H:: -1: 0: 1. That is across the sample, 50 per cent of cases *Supply chain visibility* is considered to be 'low', 0 percent 'medium', and 50 percent 'high'. These assignments can be taken to define what is meant by 'low', 'medium', and 'high'. The elicitation procedure is carried out by eliciting the following information:

1. the base, *b*
2. a weighting factor for each value of the child node
3. a weighting factor for each value of the parent nodes

During the elicitation procedure, the following values have been elicited for the different states of the nodes in the *Supply chain visibility* sub-network. The base is set to two, and the child value 'Medium' is given a weight of zero. The values 'Low' and 'High' was given the values -1 and 1, respectively. For '*Degree of contracting*' parent node, the weights assigned were 1 for low (L), 0 for medium (M), and -1 for high (H). Low values for 'Degree of contracting' are associated with high *'Supply chain visibility'*, because 'Low' state of *Supply chain visibility* is negative and 'L' state of '*Degree of contracting*' is positive. Similarly, for parent node *Quality of support*, L was assigned -1, M was assigned 0 and H was assigned 1. And for parent node *Level of confidentiality*, L, M and H were assigned 1, 0 and -1 respectively. Support material covering some basic concepts of elicitation methods was supplied to the experts prior to the interview. Although correlation and likelihood method are intuitive and understandable by experts who were most likely to have come across them, support material was intended to refresh their memory. The concepts were not discussed in detail during the elicitation interviews, however the expert was asked whether they had read the support material and understood. If the expert expressed some doubts, the basic concept of the methods were gone through.   The complete support material is available from Appendix E.

7.4 Summary and Conclusion

The scale level characterisation of uncertainties aids in categorising uncertainties as discrete or continuous nodes in the BN. Prior probability elicitation in this research was conducted using SRI elicitation protocol, where the quartiles were judged by the experts. Two different methods have been employed to populate the CPTs in the BN. Rank correlation and likelihood method have been used. This is because rank correlation method is not suitable when all the nodes in the sub-network are discrete. Rank correlation method has been widely implemented for BN which contain continuous nodes and also where they contain both continuous and discrete uncertainties. Rank correlation values are independent of the prior distributions in continuous nodes and this independence vanishes when the prior distributions are discrete. And hence, likelihood method is employed for the sub-network that contains only discrete nodes. Implementation of two different methods to derive the CPTs is a novel approach adopted in this chapter.

8 Evaluation and Validation of Bayesian Network

In the previous chapters, topics related to creating structure of the BN and the process by which inputs for the BN model were obtained was discussed. This chapter presents evaluation and validation of the BN model developed and focusses on the useful results that could be obtained. BN is integrative in nature, as it does not pertain to a single time series and therefore dataset pertaining to a future time to validate the whole model is not available (Ticehurst et al. 2007). BNs are able to produce posterior probability given evidence and provide a picture of the future but does not support validation or verification at the current time as a future dataset pertaining to a different time or scenario is not available. One of the purposes of the model is to examine the future impact from management decisions and data cannot exist for validation until such management changes have been enforced (Ticehurst et al. 2007) and sometimes the results from BNs are validated by implementing adaptive management (Henriksen and Barlebo, 2008). In the case study adopted in this research, validation has been partially carried out during building and quantification step of the BN model by industry experts (Chapter 6). The involvement of experts from industry in these steps, has provided qualitative validation of the model. Whereas, the emphasis of the type of validation in this chapter is quantitative, exploiting features of the software used. Netica can be used to perform sensitivity analysis, Most Probable Explanation (MPE) and testing with scenarios, which provide quantitative evidence with respect to model verification and validation.

This chapter presents the steps involved in modelling the BN, from fitting probability distributions to compilation of BN in Netica. The latter part of the Chapter deals with evaluation of the BN and scenario analysis. The chapter is structured as follows. Section 8.1 addresses modelling of BN, where the sub-section 8.1.1discusses the details of fitting probability distributions to quartile values elicited from experts, sub-section 8.1.2 discusses steps involved in fitting BN to Netica, by specifying prior probability distributions and populating Conditional Probability Tables (CPTs). Section 8.2 presents the evaluation of BN, including sensitivity analysis and predictive accuracy. Section 8.3 addresses scenario analysis and BNs functionality as a decision tool. Finally, Section 8.4 outlines key conclusions.

8.1 Modelling of Bayesian Network

This section dives into the steps involved in modelling of BN using a software like Netica. This section provides details relating to modelling of BN, outlining all the steps carried out and some steps take input produced in previous chapters. Netica is the software used for modelling BN here. There are several software packages available for modelling BNs. Mahjoub and Kalti (2011) discuss the various software packages dealing with BNs. Korb and Nicholson (2010) also enlist the various software packages for BN modelling in the appendix of their book. BNT, BayesiaLab, HUGIN, JavaBayes, GeNIe ,BNJ, MSBNX, SamIam, UnBBayes, ProBT, Analytica, BNet Builder, Bayes builder software, OpenBugs software, BKD/BD software, PNL and VIBES are some of the sofwares for modelling BNs (Mahjoub and Kalti, 2011; Korb and Nicholson, 2010). It is available for Windows and Mac OS versions. A free, limited demo version limited to modelling with up to 15 uncertainties and samples of 1000 cases for learning from data. It employs Expectation-Maximisation algorithm for learning the CPTs from a data set (Spiegelhalter et.al.1993). Netica does not perform structural learning and hence the user has to define the model structure. It can only perform single-finding sensitivity analysis, which means only one uncertainty at a time can have different values entered and changes in values of other uncertainties can be observed (Uusitalo, 2007). Netica also takes into consideration any new information entered into the network and performs sensitivity analysis. It is a BN software with the greatest circulation in the world which is used in finance, environment, medicine, industry and other fields (Mahjoub and Kalti, 2011; Uusitalo, 2007). It offers a graphical interface for easy operation and explores relationships between uncertainties in a model by inverting links or absorbing nodes, while keeping unchanged the probability of overall BN (Mahjoub and Kalti, 2011).

CPT is a simple table that provides a probability for each state of the child node, given the condition specified by the row (i.e. each parent node state having some value), so the probabilities of each row must sum to one. Netica does not support population of CPTs using rank correlation values or weighting factors of the likelihood method. Hence, these values have to be transformed to CPTs and for this, standalone programs such as Uninet and Bayes Table Generator are used. Uninet is a continuous and discrete non-parametric Bayesian belief net system, functioning as module of Unicorn, which is another standalone uncertainty analysis software package (Cooke et.al. 2007). It is a stand-alone program using Bayesian Belief Nets (BBNs) for stochastic modelling and for multivariate ordinal data mining available free from http://www.lighttwist.net/wp/uninet, together with supporting scientific documentation. Bayes Table Generator (Kemp-Benedict et.al. 2009) implements likelihood algorithm, where weighting factors for different states of parent nodes are elicited to derive CPTs. Uninet (Cooke et.al. 2007), takes rank correlation values and prior distributions of uncertainties as input and generates case files. These case files can be exported to Netica and used to generate CPTs. These elements of modelling are discussed in Section 8.1.2. Before that the quartile values specifying prior distributions of all the uncertainties, which was obtained in Chapter 8 are used to fit suitable parametric distributions. The prior distributions in Netica is specified using summary of PDF's such as mean, standard deviation etc. depending the type of distribution. This is discussed in Section 8.1.1. The steps in BN modelling and compiling using Netica and other softwares to support it (Uninet and Bayes Table Generator) are as follows. The steps also outline the results from previous chapters, which are used here.

i. Use quartile values obtained (Chapter 7) to fit probability distributions.
ii. Obtain summary of probability distributions using MATCH uncertainty tool (see Chapter 7).
iii. Specify prior probability distributions in Netica.
iv. Enter rank correlation values into BN sub-networks which have rank correlation method used for specifying the dependency information, using Uninet software and save the case files obtained.
v. Populate the CPTs in Netica by exporting the case files.
vi. Enter weighting factor values into *Supply chain visibility* and *Service personnel efficiency* sub-networks of the BN, where likelihood method is used for specifying the dependency information in Bayes Table Generator.
vii. Populate CPTs in Netica by exporting them from Bayes Table Generator.
viii. Compile the BN in Netica.
ix. Perform sensitivity analysis, predictive accuracy and scenario analysis in Netica

The following section presents the summary of probability distributions obtained using MATCH uncertainty tool, which was performed in the verifying step of the SRI protocol. The summary of PDF is input into Netica as prior distributions for the uncertainties. Interaction with experts was discussed in Chapter 7 as the chapter dealt with expert judgements, however the summary of PDFs are presented in this chapter to allow the reader to understand modelling better and sustain the flow of contents in the thesis.

8.1.1 Fitting Probability Distributions

The prior probabilities were elicited using quartile method (O'Hagan et.al. 2006). Many probability distributions can be fitted to the quantiles and hence some assumptions about the underlying density is inevitable (Bornkamp and Ickstadt, 2009). An assumption about the underlying prior probability distributions for all the nodes was made during elicitation procedure, which is presented in Appendix E. Hence, once the quartile values are obtained from the expert, a suitable probability distribution was fitted. For this purpose, the type of distributions fitted was based on the distribution type suggested by the experts during the elicitation process. The uncertainties, for which the expert could not suggest a probability distribution are fitted with uniform probability distribution, reflecting equal density. This was used to account for the uncertainty about the prior conditions (Marcot et.al. 2006), however it is said to give satisfactory results and is justified as the use of non-informative priors is becoming a routine in Bayesian practise (Yang and Berger, 1996).

The BN built are parametric continuous-discrete type. There are 18 continuous nodes and 12 discrete nodes in the BN built to model the factors affecting performance metrics such as *Turnaround time*. Once the quartile values are elicited from the expert, the next step involved transferring the information stated by an expert into a probability distribution. There is abundant literature on fitting distributions to datasets (Jankauskas and Mclafferty, 1996; Karian, 2010; Cousineau, 2004), however there is very sparse literature addressing transferring of expert statements about an uncertain quantity into a probability distribution. An online tool called MATCH uncertainty elicitation tool (*www.http://optics.eee.nottingham.ac.uk/match/uncertainty.php*) was used to fit PDFs because they are user friendly and reduced the time for obtaining the probability distribution parameters. They have an interactive graphical user-interface, which the expert can use if they would like to modify any values. The tool can display the parameters of the probability distribution, when 'fitting and feedback' option is chosen on the web page. The experts verified the PDFs displayed when quartiles were fed into the online tool, which was discussed in Chapter 7.

8.1.2 Compiling Bayesian Network in Netica

Implementing hybrid BNs (containing both discrete and continuous nodes) using Netica is not a straightforward case, especially if one does not intend to obtain CPTs manually which is cumbersome and employ other methods which reduce the burden of eliciting probabilities from experts. The CPTs in Netica could be manually entered, learnt from case files or datasets. Netica does not support population of CPTs using rank correlation values or weighting factors. The steps involved in exporting the CPTs derived from these methods using different software's are outlined below. Firstly, exporting CPTs from Uninet is addressed, followed by steps involved in the transfer of CPTs from Bayes Table Generator.

a) Exporting CPTs from Uninet to Netica

The BN was built in Uninet by specifying the nodes with names, type of probability distribution and the associated parameters in the Variable view of Uninet. Once, the variables were specified, BN view was chosen from the View menu. The nodes were selected from the Random variables pane and the links attached to the relevant uncertainties. Rank correlation values are entered for each arc in the network by right clicking on the node to choose 'Dependence info' option. The mode is switched to 'Sampling model' and 'Sample current BBN' option is chosen from the Sample menu. 'Sample to Netica case file' option is chosen from the dialog box and the destination folder is chosen, where the .cas file would be saved. One can also choose size of the sample in multiples of 10,000. A snapshot of the case file used for validation is shown below.

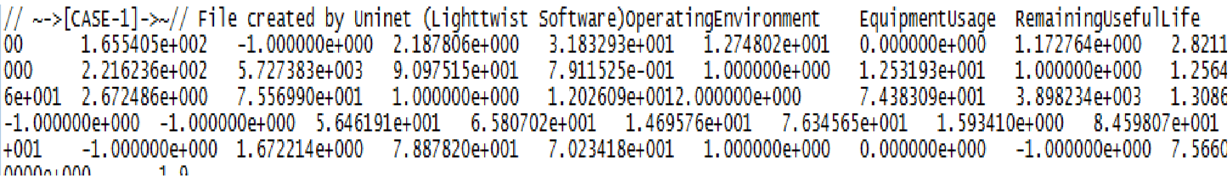

```
// ~->[CASE-1]->~// File created by Uninet (Lighttwist Software)OperatingEnvironment    EquipmentUsage  RemainingUsefulLife
00      1.655405e+002   -1.000000e+000  2.187806e+000   3.183293e+001   1.274802e+001   0.000000e+000   1.172764e+000   2.8211
000     2.216236e+002   5.727383e+003   9.097515e+001   7.911525e-001   1.000000e+000   1.253193e+001   1.000000e+000   1.2564
6e+001  2.672486e+000   7.556990e+001   1.000000e+000   1.202609e+0012.000000e+000      7.438309e+001   3.898234e+003   1.3086
-1.000000e+000  -1.000000e+000  5.646191e+001   6.580702e+001   1.469576e+001   7.634565e+001   1.593410e+000   8.459807e+001
+001    -1.000000e+000  1.672214e+000   7.887820e+001   7.023418e+001   1.000000e+000   0.000000e+000   -1.000000e+000  7.5660
```

Figure 32: A Snapshot of the Case File Created by Uninet

The same BN is then fitted in Netica with same node names and prior distributions as specified in Uninet. This BN model does not have any dependency information entered. To learn the CPTs from the sample file generated using Uninet, the case file has to be incorporated by using the option 'Incorporate case file' from the Case menu to learn the CPTs reflecting the dependency information elicited from experts. BN built in Uninet to generate case file is presented in Figure 33. The next sub-section describes the generation of CPTs using Bayes Table Generator and transferring the CPTs to Netica.

Figure 33: Bayesian Network in Uninet

b) Export of CPTs from Bayes Table Generator to Netica

Bayes Table Generator (BTG) implements likelihood method using an algorithm that uses both Bayes' rule and a simplified expression for the likelihood (Kemp-Benedict et.al. 2009). As discussed in Chapter 6, the elicitation using likelihood method would require a base *b* and weighting factor for each value of the child node and the parent nodes. A screen shot of the tool with the values for the supply chain visibility sub-network is presented in Figure 34.

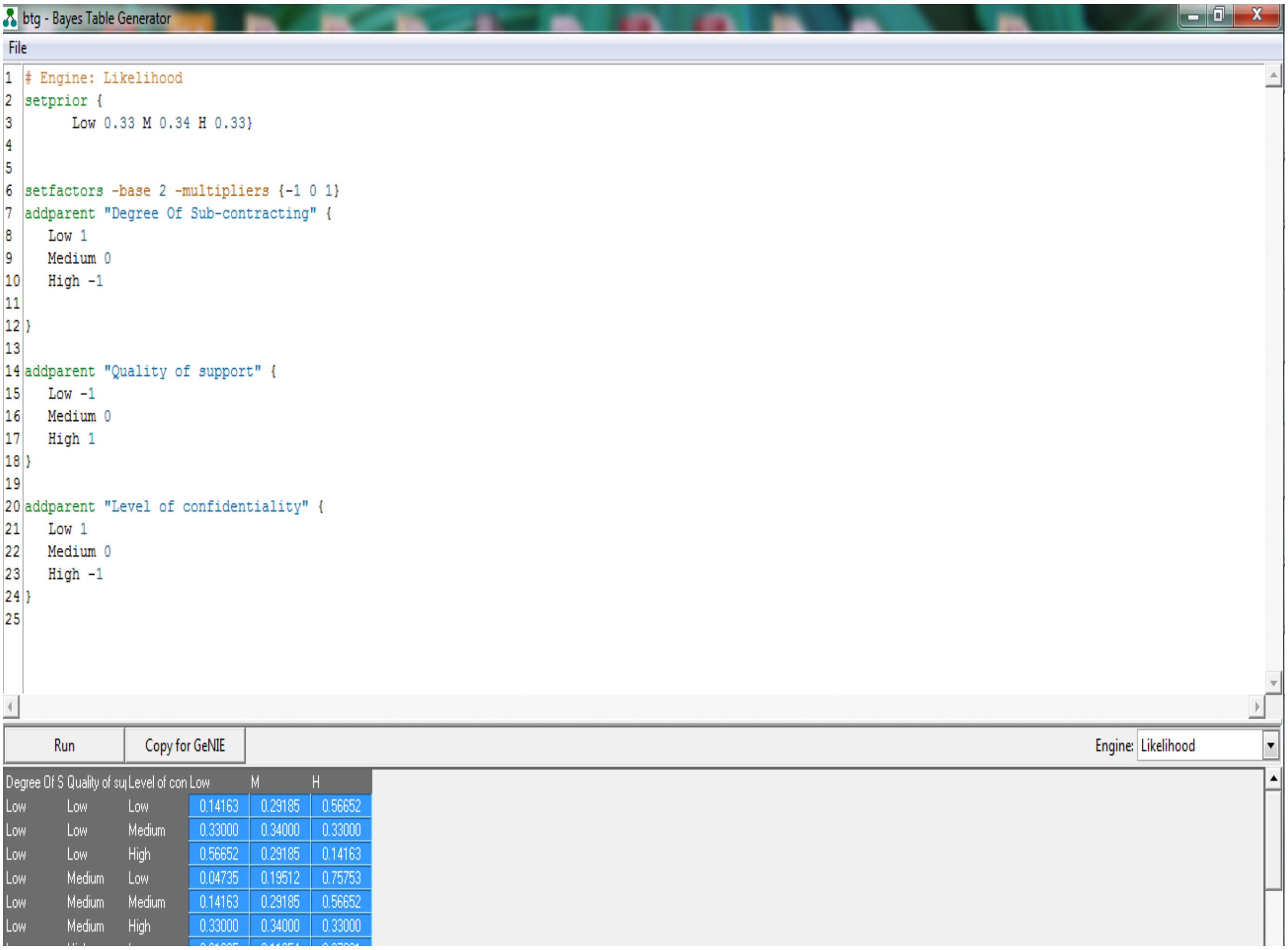


Figure 34: Snapshot of Bayes Table Generator used for Supply Chain Visibility Sub-Network

The weighting factor chosen by the experts was -1 for low, 0 for medium and 1 for high. All the parent node states were given the same weighting factor, which supports the assumption that parent nodes are independent of each other. The cells in BTG can be displayed either as numbers or as a colour map, with the darker colours indicating a higher probability. The values in the cells are transferred to the CPT in Netica. Once all the CPTs have been populated and updated, the BN is ready for making inference. BN with the updated CPTs after compilation is presented in Figure 35. In order to ensure validity, they are evaluated and tested prior to using the results from the inference. The subsequent sections addresses evaluation and scenario analysis of the BN to test whether they are behaving as expected and analyse the results produced.

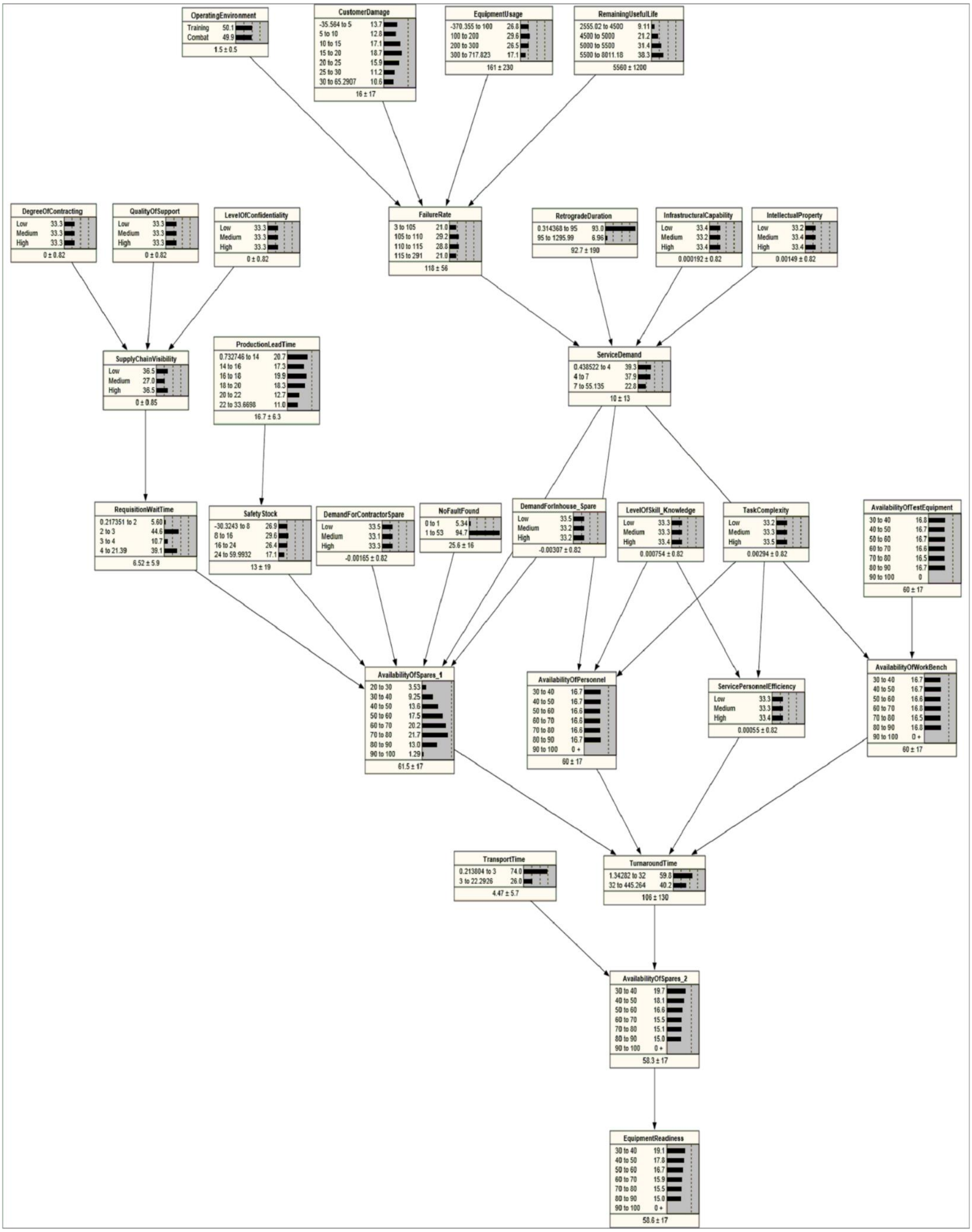


Figure 35: Compiled Bayesian Network

8.2 Evaluation of Bayesian Network

Evaluation and testing is an important aspect of any development activity (Baclawski, 2004). Quantitative evaluation of the BN is carried by testing predictive accuracy and sensitivity to findings. Followed by scenario analysis, which evaluates usefulness of BN as a decision support tool by analysing relative changes in outcome probabilities (Kragt, 2009). The evaluation done here is statistical. BN is a well-developed, sophisticated model for testing hypotheses about probability distributions, however a disadvantage of statistical hypothesis testing is that often more than one test case is required and even with a large sample of test cases the result can be ambiguous (Baclawski, 2004). Hence, further work in terms of testing with large datasets from industry and evaluation of the BN by experts from industry would enhance the reliability of the results produced by the BN. This section presents the steps and results for sensitivity analysis and predictive accuracy testing of the BN.

8.2.1 Sensitivity analysis

Sensitivity analysis tests the sensitivity of model outcomes or query nodes to variations in inputs and parameters. In Netica, one way sensitivity analysis can be carried out. Firstly, the outcome or query or target node is first selected and the option 'sensitivity to findings' from the 'network' menu is chosen. Secondly, sensitivity of key uncertainties such as *Turnaround time* is set to 30 days because Level 1 supplier has to deliver MHDD within a Turnaround time of 30 days according to the contractual arrangement set, hence variation in beliefs when Turnaround time is 30 days in looked into.

i) Sensitivity to Findings'

Sensitivity analysis for the nodes *Turnaround time* and *Equipment readiness* was carried out. The nodes are ranked in according to the degree of influence of their findings on the outcome nodes (*Turnaround time* and *Equipment readiness*) and sensitivity is calculated as measures of mutual information, variance reduction and variance in beliefs. However, variance reduction measure best describes the degree of sensitivity of one node to another (Norsys, 2014). It refers to variance of the expected real value of query node due to a finding at the varying node and it turns out to be the square of RMS change of real (Norsys, 2014). The bar graphs showing sensitivity of findings on *Turnaround time* and *Equipment readiness* nodes is shown in Figure 36 and 37. Please note that even numbered uncertainty labels are not displayed in the sensitivity analysis graph to avoid cluttering of text.

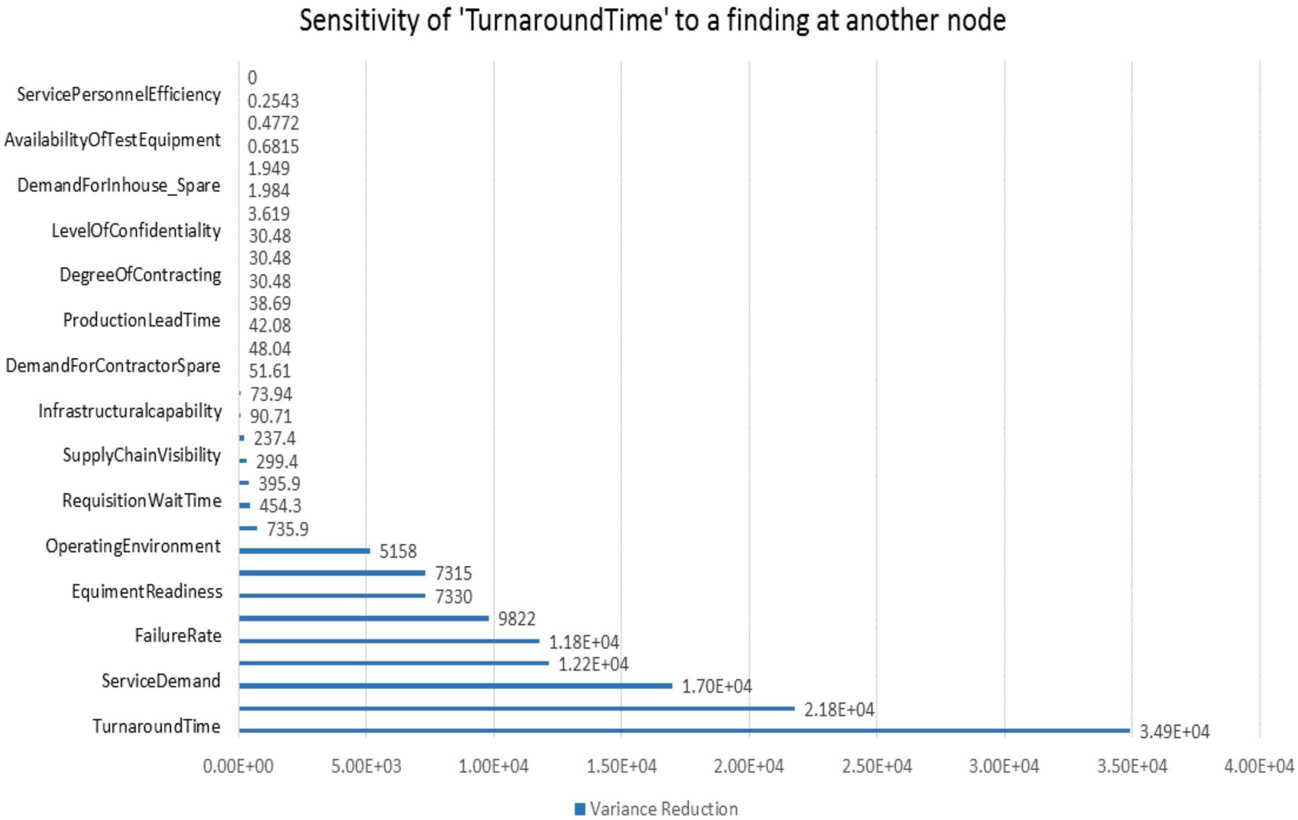


Figure 36: Sensitivity Analysis Results for Turnaround Time

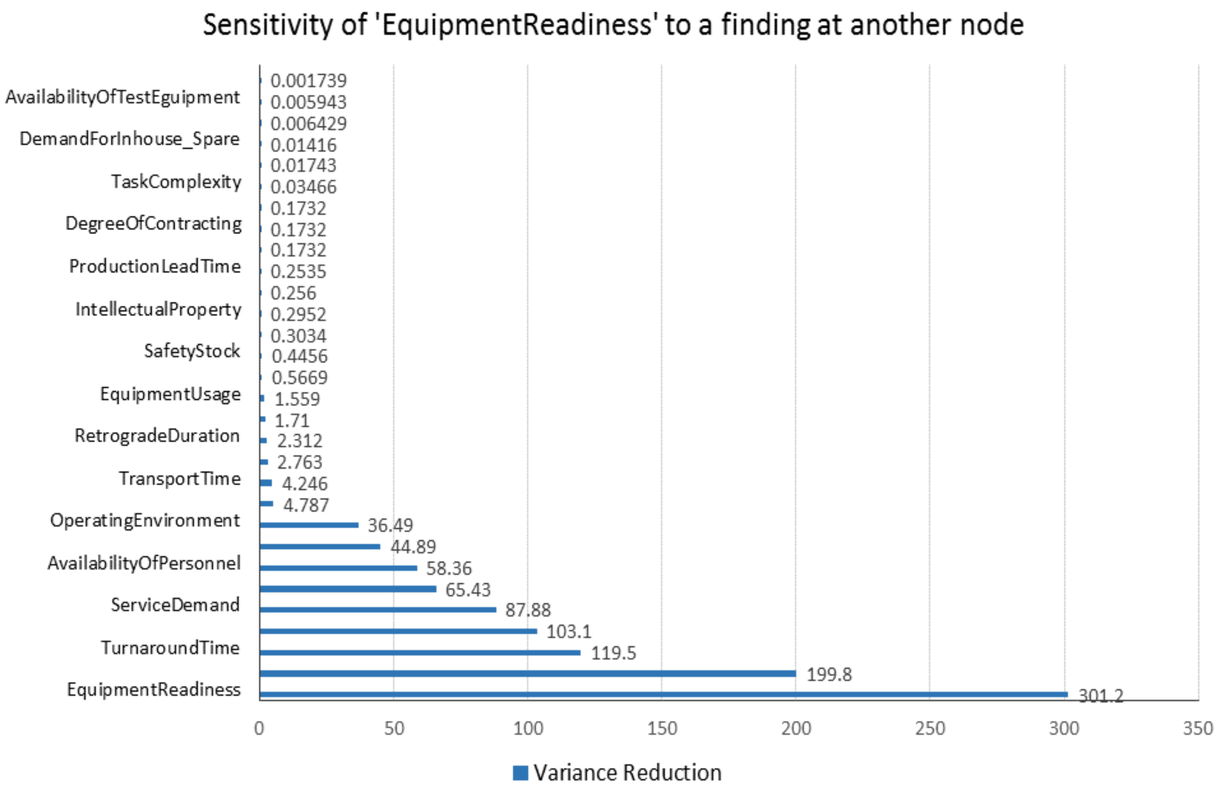


Figure 37: Sensitivity Analysis Results for Equipment Readiness

Here the most significant factors with variance reduction percentage of greater than 1% are discussed. *Availability of spares_1* (with variance reduction value of 2.18E+04) at the supplier site is the most significant factor causing largest variance reduction percentage of 62% for the node *Turnaround time*. This is in line with the information provided by experts during elicitation interviews, where they expressed *Availability of spares* as the most critical factor effecting *Turnaround time*. *Service demand, Availability of spares_2* at the customer site and *Failure rate* also show strong influence with variance reduction more than 30%. These are followed *by Availability of personnel, Equipment readiness, Availability of workbench* which display a variance reduction of greater than 20%. Followed closely by *Operating environment* with variance reduction greater than 14%. Other factors infleuncing in the range of 1% to 2% are *Customer damage, Requisition wait time* and *Retrograde duration*. *Customer damage* would influence *Turnaround time* indirectly, as the repairs falling under it are exempted from the 30 days *Turnaround time* accountability and would be an unaccountable repair where the customer would pay additional fee, if it is mutually agreed by the supplier and customer that the equipment failed due to mishandling by the customer. The low sensitivity of *Turnaround time* to *Customer damage*, *Requisition wait time* and *Retrograde duration* show that they influence *Turnaround time* minimally and are peripheral factors, which could be given some levay.

The results from the sensitivity analysis reinforces the concepts which motivated the building of BN, by the inclusion of all factors which display these concepts such as match between supply (spares, personnel, workbench) and demand (service demand, failure rate) and secondly, the alignment between the performance metrics of the supplier (*Turnaround time*) and customer (*Equipment readiness*). This is displayed by variance reduction of 21% on *Turnaround time* for any finding in the *Equipment readiness* node. Apart from the uncertainties pertaining to resources,uncertainties related to equipment reliability and uncertainties related to customers handling of the equipment such as *Operating environment* and *Retrograde duration* are also influencial factors to a lower degree (1-2%).

Sensitivity analysis with respect to *Equipment readiness* unveiled the following significant factors. The most influential factor is the *Availability of spares_2* (with variance reduction value of 199.8) with a variance reduction percentage of 66%. It is in agreement with literature and expert opinion, where the spare pool at the customer site would be used to replace any failed equipment and enhance the *Equipment readiness*. It is followed by *Turnaround time* and *Availability of spares_1* with a variance reduction of greater than 30%. Uncertainties related to demand and equipment reliability such as *Service demand* and *Failure rate* are the next significant factors with a variance reduction greater than 20%. *Availability of personnel*, *Availability of workbench* and *Operating environment* have a variance reduction value of 19%, 15% and 12% respectively. *Customer damage* and *Transport time* have a less significant variance reduction of greater than 1%. BN of the case study captures factors influencing *Turnaround time* more vividly than factors affecting *Equipment readiness* because data from customer (MOD) was very limited and hence diminished the ability to model uncertainties related to them.

ii) Sensitivity of Nodes when Turnaround Time is Equal To 30 Days

The nodes which ranked high in the sensitivity analysis for *Turnaround time* have been chosen to observe change in belief, when the *Turnaround time* is set to 30 days. This enables to optimise these uncertainties in order to achieve a *Turnaround time* of 30 days. Table 21 in Appendix F shows the change in beliefs (from the initial beliefs) when *Turnaround time* is equal to 30 days. The change in belief for *Turnaround time* has revealed that when equal to 30 days is highly sensitive to and increased the belief of *Availability of spares_1* per month at the value of 50-60% availability to 37%, increased belief for *Service Demand* of 7 to 55 MHDD per month (to 53%), increased belief for *Availability of spares_2* per month at 30-40% value to 44%, increased the belief for *Failure Rate* on a higher end value of 115-291 per year (to 45%) and even *Availability Of Personnel* at 30-40% per year (to 36%). These results further clarify the findings from sensitivity analysis. These results indicate that a *Turnaround Time* of 30 days can be achieved quite competitively even when level for *Availability of Personnel* is low at 30 to 40% and a higher *Service Demand* of 7-55 MHDD per month and a higher *Failure Rate* of 115-291 MHDD per year.

8.2.2 Predictive accuracy

Predictive accuracy refers to a quantitative evaluation of the model, by comparing model predictions with observed data (Pollino et al. 2007). It is a test which has been used to test BNs built in many areas such as ecological risk assessment, prediction of sea breeze and factors influencing wildfire occurrence (Pollino et.al. 2007; Dlamini, 2010; Kennett et.al. 2001).

The data obtained from industry was used to create test cases, against which the BN was tested. Data for nodes such as *Turnaround time*, *NFF* and *Retrograde duration* was available. A snapshot of the data for *Retrograde duration* used as case file is shown in Table 12.

Table 12: Snapshot of Test Case File for Retrograde Duration

RetrogradeDuration
157
105
13
260
13
13
2
8

The results of predictive accuracy for the three uncertainties are presented in Table 13. Data in excel format was available across a range of years ranging from as early as 2003 to mid of 2013. *Turnaround time* data was available for every receipt and collection date of the failed MHDD. NFF data was available for 6 consecutive years from 2003 to 2008. The unit of NFF is MHDDs arising due to NFF/ per year. *Retrograde duration* data was not directly available from industry. This was calculated from failure report raised date and received at supplier date. The difference between these dates was calculated using the excel function DATEDIF (start_date,end_date,unit), where failure report raised date was used as the start date and received at supplier date was used as end date. Values were calculated for *Retrograde duration* in terms of days and this was used to test the BN on its accuracy of prediction.

Table 13: Summary of Results from the Prediction Accuracy Report

Test Case	**Error Rate**	**Scoring Rules**			**Calibration**	Quality of Test				
		Logarithmic loss	Quadratic loss	Spherical payoff		Cutof	Sensitivit y	Specificity	Predictive	Predict-Neg
Turnaround time (TT)	22.69%	0.60	0.41	0.77	1.12 to 32 0-60: 77.3	0	100	0	77.3	100
						60	0	100	100	22.7
					32 to 748. 0-50: 22.7	100	0	100	100	22.7

No Fault Found (NFF)	0%	0.05	0.01	0.10	0 to 1 0-100: 0 1 to 53 0-100: 100	0 100	100 100	0 100	0 100	100 100
Retrograde duration (RD)	18.85%	0.56	0.33	0.82	0.31 to 95 0-95: 81.2 95 to 1295 0-10: 18.8	0 95 100	100 0 0	0 100 100	81.2 100 100	100 18.9 18.9

The report on predictive accuracy in Netica contains several measures which represents the BNs ability to predict. The report contains seven measures, which are confusion matrix, error rate, scoring rules, calibration, times surprised and quality of test (Norsys, 2014). The values for the various measures is represented in Table 13. Confusion matrix contains all the possible states of the test node and each case in the case file is processed to derive the most likely state i.e. the one with the highest belief. Hence, the most likely state is chosen as the prediction for the value of test node and this compared with the true value of test node. Error rate is a single measure to represent the results of confusion matrix, where the percent of cases for which the case file supplied a value, the network predicted the wrong value, where the prediction was taken as the state with highest belief (same as for the confusion matrix). The error rate was 22.69%, 0% and 18.85% for *Turnaround time*, *NFF* and *Retrograde duration* test cases respectively. This means that, for example in the *Turnaround time* test case 22.69% of the cases for which the case file supplied a *Turnaround time* value, the network predicted the wrong value, where the prediction was taken as the state with highest belief (Norsys, 2014). These results confirm the BN model's reasonable predictive power. The prediction for *NFF* test case was 0% indicating the models strong predictive power. However, this result needs to be viewed considering the small dataset used and hence, further testing with large datasets could confirm this finding.

Scoring rules such as logarithmic loss, quadratic loss and spherical payoff are also calculated in Netica. Logarithmic loss is the only scoring rule whose value is determined solely by the probability of the outcome that actually occurs (Colwell et al., 1993). For logarithmic loss (0 to infinity) and quadratic loss (0–2), scores close to zero are better. For spherical payoff (0–1), 1 indicates the best model performance (Korb and Nicholson, 2010). The logarithmic loss, quadratic loss and spherical payoff are 0.6043, 0.4122 and 0.7682 respectively for *Turnaround time* test. The logarithmic loss, quadratic loss and spherical payoff are 0.05487, 0.0057 and 0.9984 respectively for the *NFF* test, thereby indicating an excellent model performance. The logarithmic loss, quadratic loss and spherical payoff are 0.5608, 0.3342 and 0.8233 respectively for *Retrograde duration* test indicating a reasonable performance.

The column 'Calibration', indicates whether the confidence expressed by the network is appropriate (i.e. "well-calibrated") (Norsys, 2014). The results are interpreted below. In the *Turnaround time* test, its state of 1.12 to 32 days has a belief between 0-60% and 78.1% of those times it was in that state and similarly the state when *Turnaround time* is 32 to 748.7 has a belief within the range of 0-50%, 21.9% of the times the true value was that state. When the test case was run, it also indicated an increase in the bounds for *Turnaround time*, where lower value suggested was 1.12 (previously 1.34) and the higher value was expanded to 748.7 (previously 445.3 days), which indicates that *Turnaround time* range values was underestimated by the experts. In the *NFF* test case, the state 0 to 1 has a belief between 0-100% and 100% of those times it was in that state and similarly the state 1 to 53 has a belief between 0-100% and 100% of those times it was in that state. The test case file also expanded the bounds for *NFF* from 24 to 53, which indicates that *NFF* value was underestimated for its higher value by the experts. Similarly, *Retrograde duration* test case had the state 0.31 to 95 days a belief between 0- 95% and 81.2% of those times it was in that state and similarly, the state 95 to 1295 has a belief between 0-10% and 18.8% of those times it was in that state.

Times Surprised table is another table in the test case report. It is used to determine how often the network was quite confident in its beliefs, but was wrong. There are columns for being 90% confident and 99% confident (i.e. beliefs are greater than 90% or 99% respectively) that the value of the node will be a certain state, and also for being 90% and 99% confident that the value of the node will not be a certain state. This is not included as it is quite exhaustive to include in the table and also the result was 0% for most cases. As this measure largely depends on the number of test cases used, only *Retrograde duration* node showed some results because it had a larger case file. This is in line with the error rate value and hence further refinement of the BN is required to increase its predictive power and also testing with a large dataset forms a progressive next step. BN modelling is iterative in nature and researchers have even labelled the models as alpha, beta, delta and gamma model representing versions of the BN as the performance and reliability of the BN increases (Marcot, 2006). 18.85% of the time the network predicted wrong *Retrograde duration*, when it was actually confident more than 90% for it being in the state 0.31 to 95. It also showed 18.85% of the time the network predicted wrong *Retrograde duration* when it was actually 90% confident that the value of the node will not be in the state 95-1295.

Quality of test, is represented as Column 5 in Table 13. This is useful when the output of the network is going to be used to decide an action, with one action corresponding to each state of the node. However, caution has to be placed while using these results as just like the calibration table, as Netica only reports on values for which it was able to gather enough data. Therefore running the test using a greater number of cases generally results in finer divisions of the cutoff column (Norsys, 2014). The meaning of the column labels in Table 13 are as follows as given in the Norsys website:

Sensitivity = Of the cases whose actual value was the first state, the fraction predicted correctly.
Specificity = Of the cases whose actual value was the second state, the fraction predicted correctly.
Predictive Value = Of the cases the network predicted as first state, the fraction predicted correctly.
Predictive Value Negative = Of the cases the network predicted as second state, the fraction predicted correctly.

Turnaround time test has specificity and predictive value pertaining to its second state with cut-off probability of 60% and 100%. 100% of the fraction predicted correctly of the cases whose actual value was the second state. 22.69% of the cases the network predicted as second state, the fraction predicted was correctly for the same cut off probabilities. It also had 0% has the cut-off probability with 100% sensitivity and 77.31% predictive value pertaining to the first state of the *Turnaround time* node. This implies that the first state of *Turnaround time* has higher belief predicted by the BN and even the test cases with its minimum cut-off probability at 0%. For *NFF*, a cut-off belief of 100% for its first state has a sensitivity of 100% and a predictive value of 100% and its second state had the same values of 100% specificity and 100% predictive value negative for 100% cut-off probability. *Retrograde duration* had 0% cut-off probability with 100% and 81.15% sensitivity and predictive value respectively for its first state. The second state had cut-off probabilities at 95% and 100% with both having specificity value of 100% and predictive value negative of 18.85%.

8.3 Scenario Analysis

This section addresses the final step of the BN model evaluation and validation process, which is scenario analysis (Kragt, 2009). The BN model for the case study is analysed for three sets of scenarios. These scenarios have been motivated by the discussions with industry experts during interviews as well as literature, as discussed in the previous chapters. The scenarios are related to different decision-making scenarios that are faced while delivering PSS in business-to-business application. Scenario 1 is related to the whole supply chain involving level 1 supplier and OEM. Scenarios in Section 8.3.1 are related to level 1 supplier, whereas Scenarios in Section 8.3.3 are related to the customer. Scenario (1) addresses alignment of stakeholder performance metrics, which is one of the concepts based on which the BN structure was created, which is discussed in Chapter 6. Scenarios (2) and (3) are framed based on the uncertainties a particular stakeholder has control over and can take appropriate strategic or operational decisions on. Before embarking on the analysis of scenarios, Table 14 presents the context for different uncertainties used in the scenarios. Here the context is further detailed by specifying the inter or intra-organisation context within endogenous context. The context indicates the controllability and decision-making of uncertainties from the OEM perspective in the supply chain.

Table 14: Stakeholders Controllability of Uncertainties

Context	Uncertainties
Level 1 Supplier (intra-organisation)	Supply chain visibility, Turnaround time, Infrastructure capability, Safety stock
Customer (inter-organisation)	Retrograde duration, Customer damage, Operating environment, Equipment usage, Supply chain visibility

8.3.1 Scenario for Most Probable Explanation (MPE), when Turnaround time = 30 days and Equipment readiness = 95%

These are the values expected to be met under availability contracting, where no penalties are incurred. This scenario is demonstrated by using the Most Probable Explanation (MPE) feature of Netica. MPE allows one to find out the most probable configuration of values for the rest of the nodes, given findings for some nodes. It is a means to provide a plausible explanation for the observed findings and is a special case of Maximum A-posteriori Probability (MAP) (Norsys, 2014). Figure 38 below shows the BN with expected values for *Turnaround time* = 30 days and *Equipment readiness* = 95%. The MPE values for various nodes that would result in a 30 days *Turnaround time* and 95% *Equipment readiness* are shown in Table 22, which is presented in Appendix E.

For a turnaround time of 30 days and equipment readiness of 95%, availability of resources such as personnel, spares and workbench are suggested to be in the range of 70% to 90%. However, *Availability of test equipment* could fall as low as 30 to 40%. *Customer damage* should be less than 5 MHDD per year. *Degree of contracting* and *Level of Confidentiality* could be high with large number of sub-contracting of different aspects of equipment maintenance. *Equipment usage* is suggested to be less than 100 hours. Failure rate is suggested to be below 105 MHDD per year with *Operating environment* set as training. *Skill and knowledge* required to perform the service task is suggested to be low. The scenario could cope if the NFF is quite high i.e. greater than 1 and even *Requisition wait time* being greater than 4 days. *Retrograde duration* and *Transport time* is suggested to be low. *Service demand* is suggested to have a value of less than 4 MHDD per month. Hence, MPE suggests that a *Turnaround tim*e of 30 days and *Equipment readiness* of 95% can be achieved if resources such as spares and personnel be maintained at a higher end between 70 to 90% and minimal values for *Customer damage, Equipment usage, Failure rate, Level of Skill and knowledge* required to perform service task, *Retrograde duration*, *Transport time*, *Service demand and Operating environment* as training environment. It also gives scope for some uncertainties such as *Supply chain visibility, Service personnel efficiency, Quality of support* to have low states and *Level of confidentiality and Degree of contracting* to could have high states, suggesting that *Turnaround time* of 30 days and *Equipment readiness* of 95% can still be achieved if some uncertainties are not in their best state.

Hence, a *Turnaround time of* 30 days and *Equipment readiness* of 95% can be achieved even if some of the uncertainties are not in their best states such *Availability of test equipment* = 30 to 40 %, *Degree of sub-contracting* = High, *Level of confidentiality* = High, *Level of skill and knowledge* = Low and *NFF* = High. These values indicate the possible trade-off decisions that can be taken in resource planning and strategic planning.

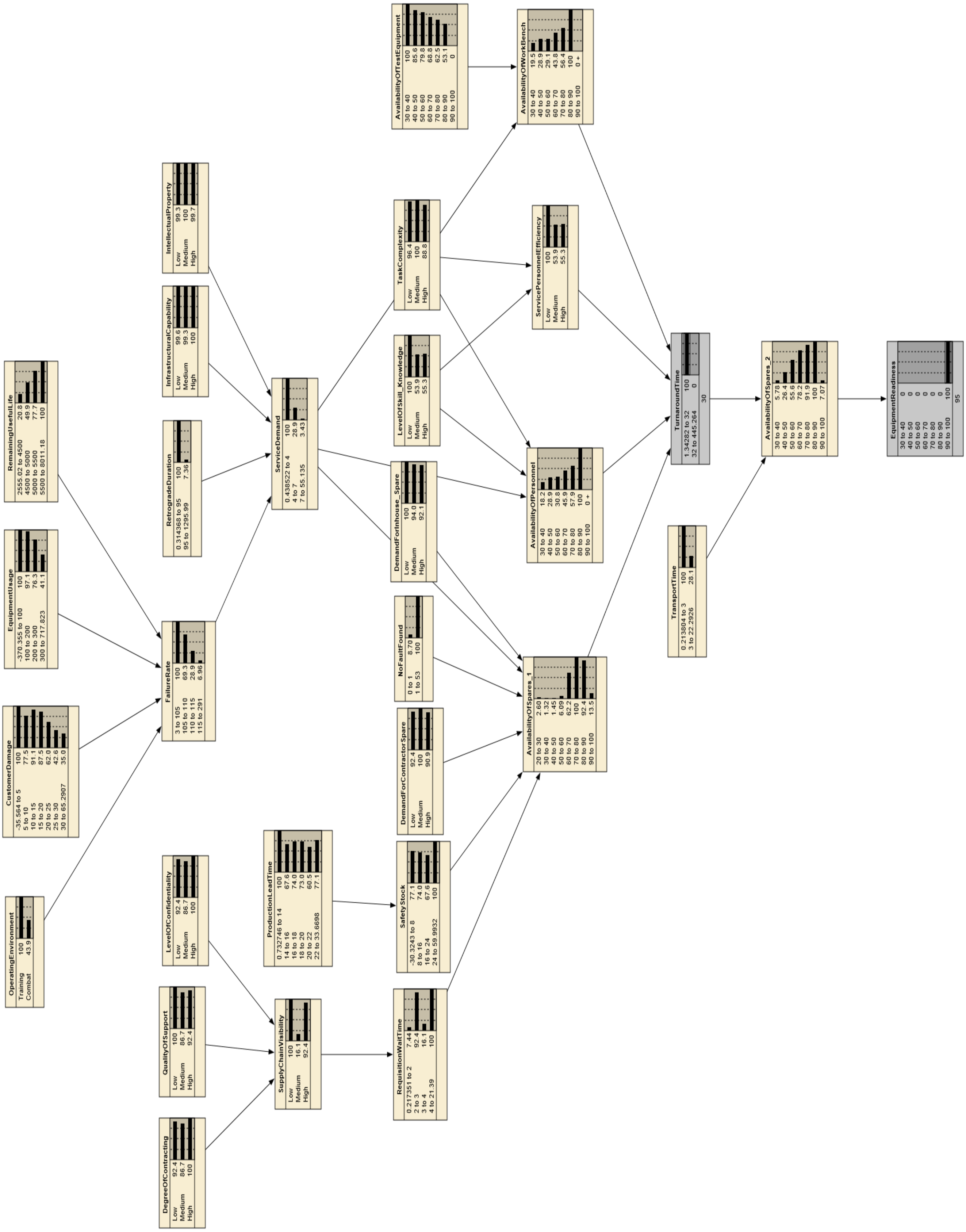


Figure 38: Scenario for MPE – Turnaround time=30 days and Equipment readiness=95%

8.3.2 Scenarios for Level 1 supplier controllable uncertainties

Three scenarios are presented which simulate various situations, where level 1supplier can control and take the appropriate strategic or operational decisions on the uncertainties.

(a) Impact of Supply chain visibility on Turnaround time

This scenario is aimed at understanding the impact of *Supply chain visibility* on *Turnaround time* and justifies strategic decision to invest in enhancing *Supply chain visibility* to contractors further down the supply chain, especially if the *Demand for contractor spares* is high. If the *Demand for contractor spares* is high but the *Supply chain visibility* is low, the mean value of *turnaround time* is 130 $\pm$ 140 days and has a 49% probability to take less than 32 days. If the *Supply chain visibility* state is high, the *Turnaround time* would be 99.4 $\pm$ 130 days and the probability of it being <32 days is 62.7%. As observed, the probability of the *Turnaround time* being < 32 days increases by 13.7% if the *Supply chain visibility* changes from low to high. It is feasible to enhance *Supply chain visibility* if an equipment has components/sub-components which is manufactured and repaired by third party suppliers at the far ends of the supply chain. Tables presenting change in beliefs on entering findings for Supply chain visibility and Demand for contractor spares is included in Appendix F.

(b) Impact of Infrastructure capability on Turnaround time

In this scenario impact of enhancing *Infrastructure capability* at the customer site is evaluated, whilst changing the beliefs of *Requisition wait time* (representing the control uncertainty for contractor supplied spares), *Safety stock* (representing the control uncertainty for in-house supplied spares), *Availability of spares_1*, *Availability of personnel* and *Availability of workbench*. The scenario is emulating a situation with nodes having the following states, where *Demand for in-house and contractor supplied spares* are in favourable states i.e. they have 'low' values, *Availability of personnel* (70-80%) who exhibit 'medium' *Service personnel efficiency*, *Availability of workbench* in the range of 70-80%. Inspite of these favourable states, *infrastructural capability* at the customer site to perform repair and maintenance has an effect on *Turnaround time*, although very slightly (0.4%) If reasonable level of infrastructural capability could be maintained by the supplier at the customer site, it would reduce the pressure in achieving *Turnaround time* of 30 days. The states of nodes such as *Requisition wait time* is low (2-3 days), *Safety stock* is maintained at 42 $\pm$ 10, *Availability of personnel* and *workbench* at 70-80%, *Service personnel efficiency* at medium, maintaining these states, and shifting

Infrastructural capability to low. *Turnaround time* was 21.2 ± 37 days and when *Infrastructural capability* is high, *Turnaround time* is 20.3 ± 33 days. There is a slight increase of 0.4% in *Turnaround time* being < 32days and *Turnaround time* is reduced from 58.2 days to 53.3 days. This demonstrates that *Infrastructural capability* of some sort at the customer site can be beneficial and would be more so when *Failure rate* are high and unpredictable or when some unexpected situations arise with transport or contractual issues. This scenario demonstrates options for a strategic decision as to whether enhancing *Infrastructure capability* at the customer site would be beneficial in the long run. Table 24 presenting change in beliefs on entering findings for infrastructural capability and maintaining favourable states for other nodes such as *Requisition wait time, Safety stock, Availability of spares_1, Availability of personnel* and *Availability of workbench* is accessible from Appendix F.

(c) Impact of Safety stock on Turnaround time

This scenario evaluates the *Safety stock* to be maintained, when the *Demand for in-house spares* is high and *Turnaround time* of 30 days is to be met. The network suggests that a *Safety stock* required to be maintained for findings when *Turnaround time* =30days and *Demand for in-house spares* is high has a mean value of 13.9 ± 19 unit with highest belief for 8 to 16 spares per month (%). This type of inference about the level of *Safety stock* to be maintained when demand is high can be useful to take operational decisions on day to day basis for volume of *Safety stock*. BNs are useful for such calculations whilst taking multiple factors into account. The future work would include adding more details to the BN, for example by obtaining numeric data for demand of spares and modelled as a continuous node. Discrete nodes can be interpreted qualitatively and hence there is ambiguity in specifying value.

8.3.3 Scenarios for Customer Controllable Uncertainties

Two scenarios are presented here and each involves different uncertainties, which the customer can control and take appropriate strategic or operational decisions on.

(a) Impact of Retrograde duration and Customer damage on Turnaround time

When *Retrograde duration* is shifted to having a high value i.e. > 95 days, it changes the *Turnaround time* to a mean value of 142 ± 140 days When the *Customer damage* node is shifted to a value >30 MHDD failures, *Turnaround time* takes the value 141 ± 140 days. So it can be seen that *Retrograde duration* affects *Turnaround time* more than *Customer damage*. When both of these nodes are set to their higher values, *Turnaround time* increases significantly to 176 $\pm$140 days. Hence, this scenario suggests that the customer should not mishandle MHDD and promptly ship the failed to MHDD to supplier.

(b) Impact of Operating environment and Equipment usage on Turnaround time

When the *Operating environment* is combat, *Turnaround time* is increased to 159$\pm$140 days. When the *Equipment usage* is chosen a high value of >300 hours per year, *Turnaround time* is increased to 124$\pm$140 days. When both these nodes are shifted to their worst state, *Turnaround time* significantly changes to 179$\pm$140 days. This shows that if the equipment is subject to adverse conditions as could be in a war, where weather, continuous high utilisation of equipment etc. would increase the frequency of breakdown of equipment. Although these parameters depends on customer use, they have less controllability even by the customer in war outbreaks. But they can provide supplier the *Equipment usage* conditions and extent of usage, so they can be prepared for the oncoming surge of failed equipment.

8.4 Conclusion

This Chapter presents detailed steps involved in compiling and evaluating the BN. The novel contribution arising from the chapter is the support for decision-making in availability contracts at strategic or operational levels. Inference from the BN supports this kind of decision-making. As the BN contains uncertainties relating to supply and demand, it can be used for optimisation of the various resources. It can also be used for analysing the degree of alignment between *Equipment readiness* and *Turnaround time* performance metrics and understand uncertainties which cause any conflict in interests among stakeholders.

Evaluation is carried out using sensitivity analysis, predictive accuracy and scenario analysis. Sensitivity analysis revealed that *Availability of spares* at the supplier site, *Service demand, Availability of spares* at customer site, *Failure rate* and *Availability of personnel* were the five significant factors effecting Turnaround time. Sensitivity analysis with respect to *Equipment readiness* unveiled the most influential factors as *Availability of spares_2* at customer site,*Turnaround time, Availability of spares_1, Service demand, Failure rate, Availability of personnel, Availability of workbench* and *Operating environment*. These results were consistent with findings from industry experts and literature. Predictive accuracy test indicated an error rate of 22.69%, 0% and 18.85% for Turnaround time, NFF and Retrograde duration test cases respectively.

In scenario analysis, three sets of scenarios were analysed. The first scenario suggested that a *Turnaround time* of 30 days and *Equipment readiness* of 95% can be achieved if resources such as spares and personnel be maintained at a higher end between 70 to 90% and minimal values for *Customer damage, Equipment usage, Failure rate*, *Level of skill and knowledge* required to perform service task, *Retrograde duration, Transport time, Service demand* and *Operating environment* as training. It further revealed that some uncertainties such as *Supply chain visibility, Service personnel efficiency, Quality of support Level of confidentiality* and *Degree of contracting* need not be in their best states, for achieving a *Turnaround time* of 30 days and Equipment readiness of 95%. The last two sets of scenarios related to stakeholders of availability contracting such as level 1 supplier and customer. The analysis suggested that customer’s actions (example by reducing damage caused to equipment by manhandling) can contribute towards better *Equipment readiness*. Sufficient information regarding the *Operating environment* and *Equipment usage* to the supplier could prepare the suppliers for higher failure rate during combat or heavy usage.

9 Conclusion

This chapter presents the conclusions drawn from conducting this research. Section 9.1 outlines the key research findings. Section 9.2 presents the conclusions drawn from this thesis. Finally, Section 9.3 presents future work.

9.1 Review of Research Findings

The research work presented in this thesis was carried out to enhance understanding and quantification of the uncertainties prevalent in PSS delivered in business to business application. It investigates uncertainty in the area of Product Service System (PSS) by proposing an approach to analyse uncertainties in PSS delivered in business-to-business application, whilst specifying a procedure to identify, characterise and model uncertainties. In pursuit of this, a comprehensive literature review was conducted research areas which are at the interface of topics such as uncertainty, PSS and availability contracts. This enabled in identification of a cohort of requirements that have not been addressed collectively in literature. It was found that PSS is inflicted with enormous uncertainties and there is a requirement to identify them in as much a comprehensive manner as possible. Another eminent requirement was the need understand the relation between uncertainties and hence, arises the requirement of prioritisation key uncertainties which is further complicated due to the complex relations between uncertainties. The modelling approach adopted was further required to be able to capture these relations between uncertainties and provide results that are easily updatable as and when new information becomes available. Another requirement pertaining to the characteristics of uncertainty was identified that would lead to providing model-based decision support. Theoretical concepts such as match between supply and demand and alignment between stakeholder goals posed themselves as interpretable as a potential requirement to be met.

Based on the findings conceived from the research gap, further developments were made to synthesise the requirements into a conceptual uncertainty framework that would provide another stepping stone enhancing our knowledge of uncertainties in PSS delivered in business-to-business applications. The following sections provide a summary of the key research findings obtained during the investigation of the proposed framework for uncertainty analysis and management.

9.1.1 The Conceptual Uncertainty Framework to Understand and Quantify Uncertainty

Based on the requirements identified in Section 2.5 of Chapter 2, a conceptual uncertainty framework was developed as presented in Chapter 3. The requirements identified were as follows.

- Identification of uncertainties in PSS as comprehensively as possible
- Capture the relation between uncertainties
- Understand characteristics of uncertainty and their influence on modelling decisions
- Ease of updating modelling results when new information is found
- Prioritisation of key uncertainties
- Representation of all uncertainties related to demand and supply in the same model space
- Visualisation of alignment between stakeholder performance metrics

These requirements were synthesized to a high level conceptual framework. Section 3.1 presents the framework which consists of four elements. They are set of uncertainties prevailing in PSS, relationship between these uncertainties, tools and techniques to treat these uncertainties proposed in the light of knowledge gained from the first two aspects of uncertainty and finally, modelling results of practical use.

It is imperative that one is not uncertain about uncertainties and hence identification of uncertainties is the foremost milestone to be pursued in understanding uncertainties. Although some work is present, where researchers have identified uncertainties, they lack in their efforts for comprehensiveness. Uncertainties expressed quantitatively and qualitatively have to given equal weights, when considering their impact on PSS delivery. There is limited research in this approach to uncertainties in PSS. Significance of relation between uncertainties grows as organisations move towards being open-systems co-existing and depending on their environment. Resource dependencies and task dependencies are the main contributors of environmental uncertainty. Tools and techniques proposed are a multi-layer uncertainty classification, which is discussed in Chapters 5 and a Bayesian Network model presented in Chapters 6, 7 and 8. Consideration of various levels of decision-making such as strategic, tactical and operational levels and embodiment of features in tools to address lack of information and lack of control was pursued. Modelling results such as the prediction of achieving performance metrics whilst considering the influence of different uncertainties and provide multiple options for decision-making in resource planning, strategic and operational planning are the key results that can be obtained.

All the above elements cumulatively addresses the third objective set out in Section 1.5.1 of Chapter 1. The framework perseveres to answer three questions mentioned in Section 1.4. What are the uncertainties in PSS, what are the characteristics of these uncertainties? and finally, what is the measure of uncertainty? It is argued that knowing answers to these questions would provide a holistic solution to uncertainty analysis and management in PSS. These key questions form inseparable elements and knowing the answer to any one or two of it would prove to be an incomplete understanding of uncertainties in PSS

9.1.2 A catalogue of Uncertainties potentially impacting the delivery of PSS

Chapter 4 presents uncertainties identified both directly and indirectly from literature. Differentiation in terminologies such as uncertainty and variables was acknowledged. Variables are regarded as prospective uncertainties, which are antecedents to understanding uncertainties. Section 4.2 enlists 133 uncertainties identified to be influential on PSS delivery. An emphasis on system perspective was placed whilst identifying the uncertainties and hence, numerous uncertainties inter-playing at the interface between product and service were identified. This was achieved by collating and searching literature related to service and maintenance of 35% (17.5% and 17.5%). The uncertainties present at the interface between product and service play a critical role in PSS, for successful design, development and delivery of PSS. There were no constraints placed on the search such as the ability to model the uncertainties. Hence, Chapter 4 presents the realisation of Objective one set out in Section 1.5.1 of Chapter 1. Variables identified here is believed to be currently the most comprehensive work capturing product, service and system element of PSS. It is of interest to acknowledge that emphasis on service and maintenance resulted in extracting higher number of uncertainties that could be categorised in the system list. As expected, more uncertainties related to service than manufacturing was found. The system perspective also sheds light on the impact of customer related uncertainties such as equipment usage, operating environment, customer damage, retrograde time and customer participation in further adding uncertainty in delivery of PSS.

9.1.3 Characteristics of uncertainty and its relevance to model-based decision support

Chapter 5 presents the multi-layer uncertainty classification. Section 5.2 explains the various characteristics of uncertainty and the way they could potentially support model-based decision support. It fulfils the second objective as set out in in Section 1.5.1 of Chapter 1. It was found that there are many uncertainty characterisation schemes proposed in literature. They are developed for a specific problem area and no consensus has been established towards a standard classification even within a specific discipline. Some of the classifications are proposed for decision making, product design, project management and modelling in general. It is argued here that uncertainties in each area are different in terms of the way they are measured, modelled and dealt with and hence, they will require a characterisation scheme specific to the modelling method or application. On the other hand, some characteristics such as cause and nature may be applicable to uncertainties in many research areas. Hence, the author is convinced that uncertainty characterisation schemes have to be tailored to the specific modelling technique at hand. Although variation of the uncertainty classification may differ slightly based on the theory the modelling technique is based on. For example, all modelling techniques based on probability theory may be sufficiently addressed by the same uncertainty classification with slight modifications.

Extensive literature analysis aided in the development of multi-layer classification. The uncertainties were propagated through an existing classification (five layer uncertainty classification proposed by Kreye et.al. (2011)) which enabled to identify the characteristics which were not addressed but found important in the context of modelling PSS delivered in business-to-business application. The multi-layer classification consists of seven characteristics such as nature (Epistemic, Aleatory, Mixture of epistemic and aleatory), context (Inter-Intra organisation, Exogenous), decision level (Strategic, Tactical, Operational), scale level (Numerical, Linguistic), effect (Manifest, Latent), cause (Direct, Indirect) and source (Process, Resource, Product, Supply chain, Customer, Contract, Organisation, Macro-economic). The various characteristics of uncertainty provide support to model-based decision as follows.

Nature of uncertainty would give an indication as to which uncertainties need further information from experts and potentially minimizing the specific uncertainty. Characterising the context of uncertainties would help to identify the linkage between different stakeholders. Hence, the key uncertainties active at the interface between stakeholders is highlighted. Characterising the context of a specific uncertainty pinpoints the source/sources of information by identifying all the stakeholders who have a stint in influencing or controlling the uncertainty. It could provide further details by specifying the name of the organisation under inter-organisation context, if the number of sub-contractors are numerous. Characterising the decision level of uncertainty would aid in identifying decision variables and aid in directing effort by the appropriate management level. Characterising the uncertainty into numerical and linguistic, helps in identifying the uncertainty as a discrete or continuous node in the BN modelling. Typically, if an uncertainty is described at the numerical scale level, it would be modelled as a continuous node in the BN. Whereas, if an uncertainty is described at the linguistic scale level, it would be defined as a discrete node in the BN. Characterising the uncertainty based on whether the effect produced by the uncertainty is observable or not observable supports in specifying some nodes as hidden or observable node in BN modelling. Cause characterisation as direct or indirect cause of a reference uncertainty unveils the structure of the BN by presenting all the uncertainty relationships. The modeller could use this information and build the structure of the BN. It could be seen as analogous to putting together a jigsaw puzzle. The relationship between a pair of uncertainties as the puzzle pieces and the BN analogous to the whole puzzle picture. Characterising the source of uncertainty maps to the different realms of the organisation and this enables to identify the job profile or profiles the experts need to be from for providing data or information about the uncertainty.

9.1.4 Bayesian Network Structure Visualising Match between Supply and Demand and Alignment between Stakeholder Performance Metrics

Chapter 6 presents the model structure, which reflects concepts such as match between supply and demand and alignment of stakeholder performance metrics. Insights from literature as well as industry was integrated to derive the various uncertainty dependencies. These uncertainty dependencies were organised together to form the structure of BN. The information from literature was analysed in four steps motivated from text mining. The four steps carried out include literature gathering, literature pre-processing, literature analysis and visualisation. Co-occurrence analysis was carried out to determine the frequency of occurrence of relation between uncertainties in literature. The insights from industry was obtained at various occasions, which include industry visits, steering meetings and working meetings. An initial validation called face validity of the BN structure was conducted using likert scale scoring. Assumptions were formulated to neutralise the effects of information and data paucity and modelling flexibility. The insights from literature and industry was merged by mapping clusters of uncertainty to the various activities represented in the IDEFO maps. These research findings address the fourth objective of research, which was to determine how uncertainties impact on the delivery of PSS in business-to-business application. The BN structure initiates the process to finding the influence uncertainties have on PSS delivery.

9.1.5 Capturing Expert Knowledge as Input to Bayesian Network Model

Chapter 7 presents the methods and procedure adopted to obtain input to compile the BN in Netica. It was found that BN which contain both discrete and continuous nodes i.e. hybrid BN require different methods to elicit data from experts. Former method is used when most of the nodes involved in the sub-network are continuous uncertainties and some discrete nodes i.e. a hybrid BN, whereas the latter method is adopted when all the nodes involved were discrete uncertainties. Rank correlation method is not suitable when all the nodes in the sub-network are discrete. because the measures of association between continuous random uncertainties can be expressed in terms of the corresponding copula only and are thus independent of the marginal distributions, however these interrelationship fails as soon as there are discontinuities in the marginal distribution functions (Neslehova, 2007). In other words, rank correlation values are independent of the continuous marginal distributions of the parent and child node, however this independency ceases when a discrete nodes are present. Hence, likelihood method is used to capture dependencies between uncertainties in sub-networks containing discrete nodes. These research findings again address Objective four, which was to determine how uncertainties impact on the delivery of PSS in business-to-business application.

9.1.6 Modelling Results to Support Decision-Making in PSS

Chapter 8 presents the modelling results obtained through evaluation and validation of the Bayesian Network. Sensitivity analysis revealed that *Availability of spares_1* at the level-1 supplier facility is the most influential uncertainty affecting *Turnaround time* with a variance reduction of 62%. The other uncertainties affecting *Turnaround time* are *Service demand, Availability of spares_2* at the customer site and *Failure rate.* On the other hand, uncertainties such as *Customer damage*, *Requisition wait time* and *Retrograde duration* show minimal influence on *Turnaround time*. Sensitivity analysis with respect to *Equipment readiness* unveiled the following significant factors. The most influential factor is the *Availability of spares_2* (with variance reduction value of 199.8) with a variance reduction percentage of 66%. It is followed by *Turnaround time* and *Availability of spares_1* with a variance reduction of greater than 30%. Uncertainties related to demand and equipment reliability such as *Service demand* and *Failure rate* are the next significant factors with a variance reduction greater than 20%. *Customer damage* and *Transport time* have a less significant variance reduction of greater than 1%. Scenario Analysis peformed when *Turnaround time* is equal to 30 days is highly sensitive to and increased the belief of *Availability of spares_1, Availability of spares_2, Failure Rate* and even *Availability Of Personnel*. These results further clarify the findings from sensitivity analysis. These results indicate that a *Turnaround Time* of 30 days can be achieved quite competitively even when level for *Availability of Personnel* is low at 30 to 40% and a higher *Service Demand* of 7-55 MHDD per month and a higher *Failure Rate* of 115-291 MHDD per year. Another scenario with *Turnaround tim*e equal to 30 days and *Equipment readiness* of 95% showed that these performance metrics can be achieved, if resources such as spares and personnel be maintained at a higher end between 70% to 90% inspite of unfavourable state of some uncertainties. *Availability of test equipment*, *Supply chain visibility, Service personnel efficiency, Quality of support, Level of skill and knowledge* could be in low states and *NFF, Level of confidentiality and Degree of contracting* could have high states, suggesting that *Turnaround time* of 30 days and *Equipment readiness* of 95% can still be achieved if some uncertainties are not in their best state. These values indicate the possible trade-off decisions that can be taken in resource planning and strategic planning. It was also found that *Supply chain visibility* increases the belief of *Turnaround time* being less than 32 days, hence it is feasible to enhance *Supply chain visibility* if an equipment has components/sub-components which is manufactured and repaired by third party suppliers at the far ends of the supply chain. *Infrastructural capability* at the customer site to perform repair and maintenance has an effect on *Turnaround time,* hence if reasonable level of infrastructural capability could be maintained by the supplier at the customer site, it would reduce the pressure in achieving *Turnaround time* of 30 days. Especially if *Failure rate* are high and unpredictable or when some unexpected situations arise with transport or contractual issues, the strategic decision to enhance *Infrastructure capability* at the customer site would be beneficial in the long run. A scenario analysis about the level of *Safety stock* to be maintained when demand is high is useful to take operational decisions on day to day basis for volume of *Safety stock.* It was also found that *Retrograde duration* affects *Turnaround time* more than *Customer damage*. Hence, this scenario suggests that the customer should not mishandle MHDD and promptly ship the failed MHDD to supplier for repair in order to achieve the required performance metric. *Operating environment* and *Equipment usage* also impact *Turnaround time.* The frequency of breakdown of MHDD increases if the equipment is subject to adverse conditions as could be in a war, where weather conditions, continuous high utilisation of equipment etc. are beyond the customers control. However having this information about *Equipment usage* conditions and extent of usage etc., can prepare service providers for the oncoming surge of failed equipment.

9.1.7 Novel Aspects of Research Work

This research work has made various contributions towards understanding and quantifying uncertainties in PSS and provided a step towards a conceptual uncertainty framework, which can be implemented in different fields addressing uncertainty. The applicability of the conceptual framework to a realistic setting is novel in itself. The following points highlight the key novel aspects of this research work.

- A novel conceptual uncertainty framework. There are many conceptual frameworks existent in literature, where most of them have not taken wings into practical implementation. However, the conceptual uncertainty framework proposed in this research is innovative in its ability for full-fledged implementation to a practical industrial application using a case study approach. This can be seen in subsequent chapters of the thesis (Chapters 4,5,6,7 and 8) where each element of the conceptual framework has been implemented using an industry case study and potentially useful modelling results are obtained in the end.

- Differentiation between uncertainty and variable is exploited to reveal a comprehensive list of uncertainties. The two terms are often used inter-changeably and in this work the difference between the two terms are acknowledged, whilst identifying the uncertainties.

- 133 uncertainties are identified from literature directly and indirectly from a procedure adapted from text mining. It is the most comprehensive list of uncertainties identified pertaining to PSS delivered in business-to-business applications.

- The multi-layer uncertainty classification is a scheme of characterising uncertainties and producing cues to model-based decision support. It is a novel approach in uncertainty characterisation as it is formulated to support modelling technique employed to quantify the uncertainties in a pragmatic manner. This is done mainly by providing suggestions to various decisions the modeller is faced with.

- A BN structure derived from insights from literature and expert knowledge. Various approaches to derive BN structure have been proposed, which include expert knowledge, data, literature etc. However, combination of expert knowledge and literature to build BN structure was not found in literature.

- A unique concept-based BN structure. The BN structure reflects two unique underlying concepts. Inclusion of theoretical concepts such as, match between supply and demand and alignment of performance metrics of different stakeholders, evidence the application of BN to concept-oriented modelling rather than mundane cause-effect modelling. Some uncertainty relations, for example relation between *Intellectual property* and *Supply chain visibility*, identified are novel identified from case study of this research. Here the BN structure brings service provision aspect of availability contracts to the forefront. It emphasises factors which the PSS provider has to consider unlike in manufacturing due to characteristics of service such as its inability to be inventoried, high degree of interaction between service provider and customer, non-portability of service and the intangible nature of service output.

- Rank correlation method and likelihood method to capture the CPT's. Implementation of two different methods to derive the CPTs is a novel approach adopted in this chapter. It heavily reduces extraneous calculations and is suitable to obtain the initial CPTs.

- The modelling results included several scenario analysis and sensitivity analysis, which could potentially provide industrial solutions, by prescribing range of values for various uncertainties given findings at other uncertainties to achieve performance outcomes in availability contracts. This involved analysing and visualising uncertainties relating to the nexus of different stakeholders such as OEM (Original Equipment Manufacturer), supplier and customer. BN has not been used to model availability contracts and PSS. Hence, the type of results provided by the model can be directly used and interpretable by decision-makers

9.2 Conclusions

The research work reported in this thesis has demonstrated the potential of three aspects of uncertainty (identification, characterisation and model) to support decision-making in PSS delivered in business-to-business applications. It is evident from this research that uncertainties, their characteristics and subsequent modelling are inseparable aspects, where all need to be known in order to enhance our understanding of uncertainties. The following paragraphs provide key conclusions drawn from this research work.

- The comprehensive literature review has shown the key requirements that need to be met in order to enhance understanding and quantifying uncertainties in PSS. Exploiting characteristics of uncertainty and a modelling technique which can capture relation between uncertainties and has the ability to update results in the light of new information are potential aspects that need to be explored.

- The conceptual uncertainty framework synthesised from the requirements identified in literature provides a bird's eye view of the elements that need to be considered to address uncertainties in PSS. The generic high level model guides modellers and/or analysts to consider the approaches and methods to capture uncertainties, analyse the uncertainty characteristics for deeper understanding and subsequently employ a suitable modelling technique to produce useful modelling results.

- It was found that high number of uncertainties identified could be categorised under system list. Hence, PSS is effected by uncertainties which connect product and service elements unlike in pure manufacturing or service organisations. It also sheds light on the impact of customer related variables such as equipment usage, operating environment, customer damage, retrograde time and customer participation of PSS in triggering demand for service.

- It was found that seven characteristics of uncertainty such as nature, context, scale level, decision level, effect, cause and source are significant for a deeper understanding of uncertainties in PSS. They provide support to model-based decision support by identifying key stakeholders who could provide further information related to uncertainties in a complex supply chain, suitable mathematical representation of the uncertainty, information to derive model structure and identification of industry personnel who could provide tacit knowledge regarding the uncertainty.

- Compiling of the BN revealed that *Availability of spares_1* at the supplier site as the most influencing uncertainty on *Turnaround Time*, whereas Ava*ilability of spares_2* at customer site as most influentuial uncertainty affecting *Equipment Readiness*. It was also found that a *Turnaround time* of 30 days and *Equipment readiness* of 95% can be achieved if resources such as spares and personnel are maintained at a higher end between 70 to 90% and on the other hand, some uncertainties such as *Supply chain visibility, Service personnel efficiency, Quality of support Level of confidentiality* and *Degree of contracting* need not be in their best states.

- Scenario's related to customer suggested that customer's actions (example by reducing damage caused to equipment) can contribute towards achieving suppliers performance metric, which in turn could benefit them in better *Equipment readiness*. Sufficient information regarding the *Operating environment* and *Equipment usage* to the supplier could prepare the suppliers for higher failure rate during combat or heavy usage.

9.3 Future Work

The findings from this research provides opportunities for future work in various areas. In particular, the areas of decision making in availability contracts, uncertainty and PSS in general. In this research, the conceptual uncertainty framework is applied to an industry case study and this could be further extended to implementing the results in "real-life" decision-making at strategic, tactical and operational levels. This would give an indication to the various improvements that could be incorporated into the conceptual framework and the procedure followed to apply it to the case study. Future research is needed to further validate the BN framework of the uncertainties influencing performance metrics of the various stakeholders. BN could be trained and evaluated with huge datasets, which would increase the accuracy of predictions. Verification of these findings and incorporation of any new findings to update modelling results would support the same. There is potential for further work in terms of a more detailed understanding of the customer's role in availability contracts. Further knowledge to the uncertainties faced by the customer and also looking closer at the uncertainties of primary service provider would produce a more holistic picture of the MHDD repair and delivery process. In the area of uncertainty further validation of characterisation of uncertainties using the multi-layer classification could be realised by the involvement of uncertainty modellers from industry. All the assumptions made in this research could be tested, for example considering all uncertainties as epistemic and employ appropriate expert elicitation approach based on the nature of uncertainty, as discussed in Chapter 6. Verification of these findings and incorporation of any new findings to train and update the BN modelling results. Future research is needed to further validate the BN framework of the uncertainties influencing performance metrics of the various stakeholders. BN could be trained and evaluated with huge datasets, which would increase the accuracy of predictions. Verification of these findings and incorporation of any new findings in future to update modelling results would support the same purpose. There is potential for further work in terms of a more detailed understanding of the customer's role in availability contracts, as this has been limited in the current research. Further knowledge to the uncertainties faced by the customer and also looking closer at the uncertainties of primary service provider would produce a more holistic picture of the MHDD repair and delivery process. It would also be interesting to employ Dynamic Bayesian Networks to model uncertainties whilst capturing their dynamic characteristic and this would enable to compare it to other modelling techniques such as Agent Based Modelling, which have been implemented currently to capture dynamism in uncertainties.

References

ABBAS, A.E., BUDESCU, D.V., YU, H. and HAGGERTY, R., 2008. A Comparison of Two Probability Encoding Methods: Fixed Probablity vs. Fixed Variable Values.

ALA-RISKU, T. Installed base information management with industrial service operations *18th Annual Conference*, 2007.

ALBANO, G.L., CALZOLARI, G., DINI, F., IOSSA, E. and SPAGNOLO, G., 2006. Procurement contracting strategies. *Handbook of Procurement*, pp. 8.

ALE, B., L. BELLAMY, A. ROELEN, R. COOKE, L. GOOSSENS, A. HALE, D. KUROWICKA and E. SMITH. Development of a causal model for air transport safety *ASME 2005 International Mechanical Engineering Congress and Exposition*, 2005.

AMES, D., NEILSON, B., STEVENS, D. and LALL, U., 2005. Using Bayesian networks to model watershed management decisions: an East Canyon Creek case study. *Journal of Hydroinformatics*, vol. 7, pp. 267-282.

ANANDKUMAR, A., HSU, D., JAVANMARD, A. and KAKADE, S.M., 2012. Learning Topic Models and Latent Bayesian Networks Under Expansion Constraints. *ArXiv Preprint arXiv:1209.5350*.

ANG, G., T. BAINES and H. LIGHTFOOT. A Methodology for Adopting Product Service Systems as a Competitive Strategy For ManufacturerAnonymous *Proceedings of the 2nd CIRP International Conference on Industrial Product/Service Systems, Linköping University, Linköping, Sweden*, 2010.

ANTAL, P. and A. MILLINGHOFFER. Literature Mining using Bayesian Networks. *Probabilistic Graphical Models*, 2006.

ANTAL, P., FANNES, G., DE MOOR, B. and MOREAU, Y., 2002. Using domain literature and data to annotate and learn Bayesian networks.

ANTAL, P., FANNES, G., TIMMERMAN, D., MOREAU, Y. and DE MOOR, B., 2004. Using literature and data to learn Bayesian networks as clinical models of ovarian tumors. *Artificial Intelligence in Medicine*, vol. 30, no. 3, pp. 257-281.

APPLICATION, Netica., 2014. *Norsys Software Corp.*

ARMISTEAD, C. and CLARK, G., 1993. A Framework for Formulating After-sales Support Strategy. *International Journal of Physical Distribution & Logistics Management*, vol. 21, no. 9, pp. 22-29 ISSN 0960-0035.

ARMISTEAD, C. and CLARK, G., 1994. The “coping” capacity management strategy in services and the influence on quality performance. *International Journal of Service Industry Management*, vol. 5, no. 2, pp. 5-22.

ASIEDU, Y. and GU, P., 1998. Product life cycle cost analysis: state of the art review. *International Journal of Production Research*, vol. 36, no. 4, pp. 883-908.

AURICH, J.C., FUCHS, C. and WAGENKNECHT, C., 2006. Life cycle oriented design of technical Product-Service Systems. *Journal of Cleaner Production*, vol. 14, no. 17, pp. 1480-1494 ISSN 0959-6526. DOI 10.1016/j.jclepro.2006.01.019.

Australian National Audit Office., 1998. *Life cycle Costing in the Department of Defence.* Canberra, Australian: National Audit Office.

AYYUB, B.M. and KLIR, G.J., 2006. *Uncertainty modeling and analysis in engineering and the sciences.* CRC Press.

BACLAWSKI, K. Bayesian network development Anonymous *International Workshop on Software Methodologies, Tools and Techniques,* 2004.

BAINES, T., LIGHTFOOT, H. and KAY, J., 2009a. Servitized manufacture: Practical challenges of delivering integrated products and services. *Proceedings of the Institution of Mechanical Engineers, Part B: Journal of Engineering Manufacture*, vol. 223, no. 9, pp. 1207-1215.

T.S. Baines, H.W. Lightfoot, BENEDETTINI, O. and J.M. Kay, 2009 b. The servitization of manufacturing: A review of literature and reflection on future challenges. *Journal of Manufacturing Technology Management*, vol. 20, no. 5, pp. 547-567 ISSN 1741-038X.

BAINES, T., LIGHTFOOT, H.W., EVANS, S., NEELY, A., GREENOUGH, R., PEPPARD, J., ROY, R., SHEHAB, E., BRAGANZA, A. and TIWARI, A., 2007. State-of-the-art in product-service systems. *Proceedings of the Institution of Mechanical Engineers, Part B: Journal of Engineering Manufacture*, vol. 221, no. 10, pp. 1543-1552.

BAKER, S. and E. MENDES. Assessing the weighted sum algorithm for automatic generation of Probabilities in Bayesian NetworksAnonymous *Information and Automation (ICIA), 2010 IEEE International Conference on*, 2010.

BANKOLE, O., R. ROY, E. SHEHAB and P. WARDLE. Affordability Assessment of Industrial Product-Service System in the Aerospace Defence IndustryAnonymous *Proceedings of the 19th CIRP Design Conference–Competitive Design*, 2009.

BANKOLE, O.O., 2011. Development of an affordability assessment framework for defence contracts at the bidding stage.

BARABADY, J. and KUMAR, U., 2007. Availability allocation through importance measures. *International Journal of Quality & Reliability Management*, vol. 24, no. 6, pp. 643-657 ISSN 0265-671X. DOI 10.1108/02656710710757826.

BARQUET, A., CUNHA, V., OLIVEIRA, M. and ROZENFELD, H., 2011. Business Model Elements for Product-Service System. In: J. HESSELBACH and C. HERRMANN eds., Springer Berlin Heidelberg,01/01, pp. 332-337 ISBN 978-3-642-19688-1. DOI 10.1007/978-3-642-19689-8_58.

BARTH, A., E. CAILLAUD and B. ROSE. How to validate research in engineering design?Anonymous *DS 68-2: Proceedings of the 18th International Conference on Engineering Design (ICED 11), Impacting Society through Engineering Design, Vol. 2: Design Theory and Research Methodology, Lyngby/Copenhagen, Denmark, 15.-19.08. 2011*, 2011.

BAXTER, D., ROY, R., DOULTSINOU, A., GAO, J. and KALTA, M., 2009. A knowledge management framework to support product-service systems design. *International Journal of Computer Integrated Manufacturing*, vol. 22, no. 12, pp. 1073-1088.

BEAMON, B.M., 1998. Supply chain design and analysis:: Models and methods. *International Journal of Production Economics*, 8/15, vol. 55, no. 3, pp. 281-294 ISSN 0925-5273. DOI http://dx.doi.org/10.1016/S0925-5273(98)00079-6.

BIANCHI, N.P., EVANS, S., REVETRIA, R. and TONELLI, F., 2009. Influencing factors of successful transitions towards product-service systems: a simulation approach. *International Journal of Mathematics and Computers in Simulation*, vol. 3, no. 1, pp. 30-43.

BOBBIO, A., PORTINALE, L., MINICHINO, M. and CIANCAMERLA, E., 2001. Improving the analysis of dependable systems by mapping fault trees into Bayesian networks. *Reliability Engineering & System Safety*, 3, vol. 71, no. 3, pp. 249-260 ISSN 0951-8320. DOI http://dx.doi.org/10.1016/S0951-8320(00)00077-6.

BOONE, H.N. and BOONE, D.A., 2012. Analyzing likert data. *Journal of Extension*, vol. 50, no. 2, pp. 1-5.

BORNKAMP, B. and ICKSTADT, K., 2009. A Note on B-Splines for Semiparametric Elicitation. *The American Statistician*, 11/01; 2014/09, vol. 63, no. 4, pp. 373-377 ISSN 0003-1305. DOI 10.1198/tast.2009.08191.

BOWEN, G., 1993. Taking the unpredictability out of military aircraft maintenance. *Aircraft Engineering and Aerospace Technology*, vol. 68, no. 2, pp. 10-13 ISSN 0002-2667. DOI 10.1108/eb037627.

BRAUNER, M.K. and LACKEY, A., 2003. *CWT and RWT Metrics Measure The Performance Of The Armys Logistics Chain For Spare Parts.* RAND Corporation.

BREZET, J., BIJMA, A., EHRENFELD, J. and SILVESTER, S., 2001. The design of eco-efficient services. *Delft University of Technology, Design for Sustaianblity Program, Delft*.

BRYMAN, A., 2012. *Social research methods.* Oxford university press.

BUNTINE, W. Theory refinement on Bayesian networksAnonymous *Proceedings of the Seventh conference on Uncertainty in Artificial Intelligence*, 1991.

BUNTINE, W.L., 1996. A guide to the literature on learning probabilistic networks from data. *Knowledge and Data Engineering, IEEE Transactions on*, vol. 8, no. 2, pp. 195-210 ISSN 1041-4347. DOI 10.1109/69.494161.

BURGMAN, M., FIDLER, F., MCBRIDE, M., WALSHE, T. and WINTLE, B., 2006. Eliciting expert judgments: literature review.

CALDWELL, N.D. and SETTLE, V., 2011. Incentives and Contracting for Availability: Procuring Complex Performance. *Complex Engineering Service Systems*, pp. 149-162.

CANO, A., MASEGOSA, A.R. and MORAL, S., 2011. A method for integrating expert knowledge when learning Bayesian networks from data. *Systems, Man, and Cybernetics, Part B: Cybernetics, IEEE Transactions on*, vol. 41, no. 5, pp. 1382-1394.

CATULLI, M., 2012. What uncertainty? Further insight into why consumers might be distrustful of product service systems. *Journal of Manufacturing Technology Management*, vol. 23, no. 6, pp. 780-793.

CHASE, R.B., 1981. The Customer Contact Approach to Services: Theoretical Bases and Practical Extensions. *Operations Research*, vol. 29, no. 4, pp. pp. 698-706 Copyright © 1981 INFORMS. ISSN 0030364X.

CHEN, C., 2000. Extensions of the TOPSIS for group decision-making under fuzzy environment. *Fuzzy Sets and Systems*, 8/16, vol. 114, no. 1, pp. 1-9 ISSN 0165-0114. DOI http://dx.doi.org/10.1016/S0165-0114(97)00377-1.

CHIRUMALLA, K., BERTONI, A., ERICSON, Å. and ISAKSSON, O., 2013. Knowledge-sharing network for product-service system development: Is it atypical? In: *The Philosopher's Stone for Sustainability*Springer, pp. 109-114.

CHOI, E. and NICULESCU, S., 2006. The impact of US export controls on the Canadian space industry. *Space Policy*, vol. 22, no. 1, pp. 29-34.

CLEMEN, R.T. and REILLY, T., 1999. Correlations and copulas for decision and risk analysis. *Management Science*, vol. 45, no. 2, pp. 208-224.

CLEMEN, R.T., FISCHER, G.W. and WINKLER, R.L., 2000. Assessing dependence: Some experimental results. *Management Science*, vol. 46, no. 8, pp. 1100-1115.

COBB, B.R., RUMI, R. and SALMERON, A., 2007. Bayesian network models with discrete and continuous variables. In: *Advances in Probabilistic Graphical Models*Springer, pp. 81-102.

COLEN, P. and M. LAMBRECHT. Product service systems as a vehicle for sustainability: exploring service operations strategiesAnonymous *Proceedings of the 3rd International Conference on Information Systems, Logistics and Supply Chain (ILS 2010)*, 2010.

COLOSI, L., ROTHROCK, L., BARTON, R., BANKS, J. and REICHARD, K., 2010. Effects of Personnel Availability and Competency on Fleet Readiness

COOKE, R., KUROWICKA, D., HANEA, A., MORALES, O., ABABEI, D., ALE, B. and ROELEN, A., 2007. Continuous/discrete non parametric bayesian belief nets with unicorn and uninet. *Proceedings of Mathematical Methods in Reliability MMR*.

COOKE, R.M., 1991. Experts in uncertainty: opinion and subjective probability in science.

COUSINEAU, D., BROWN, S. and HEATHCOTE, A., 2004. Fitting distributions using maximum likelihood: Methods and packages. *Behavior Research Methods, Instruments, & Computers*, vol. 36, no. 4, pp. 742-756.

COWELL, R.G., DAWID, A.P. and SPIEGELHALTER, D.J., 1993. Sequential model criticism in probabilistic expert systems. *Pattern Analysis and Machine Intelligence, IEEE Transactions on*, vol. 15, no. 3, pp. 209-219.

CRAIGHEAD, C.W., BLACKHURST, J., RUNGTUSANATHAM, M.J. and HANDFIELD, R.B., 2007. The severity of supply chain disruptions: design characteristics and mitigation capabilities. *Decision Sciences*, vol. 38, no. 1, pp. 131-156.

CRAWFORD, M., and Stewart, J, K., 2012. Writing an escalation contract using the Consumer Price Index. *Beyond the Numbers: Prices & Spending*, vol. 1, no. 19 [viewed April 2013]. Available from: http://www.bls.gov/opub/btn/volume-1/writing-an-escalation-contract-using-the-consumer-price-index.htm.

CURRIER, D.P., 1979. *Elements of research in physical therapy*. Williams, \& Wilkins.

CUTHBERT, R., TIWARI, A., BALL, P.D., THORNE, A. and MCFARLANE, D., 2011. Investigating the role of information on service strategies using discrete event simulation. In: *Complex Engineering Service Systems*Springer, pp. 197-214.

DALTON, A., BROTHERS, A., WALSH, S., WHITE, A. and WHITNEY, P., 2012. 10 Expert elicitation method selection process and method comparison. *Neuroscience and the Economics of Decision Making*, vol. 5, pp. 182.

DALY, R., SHEN, Q. and AITKEN, S., 2011. Learning Bayesian networks: approaches and issues. *The Knowledge Engineering Review*, vol. 26, no. 02, pp. 99-157.

DANTAN, J.Y., GAYTON, N., QURESHI, A.J., LEMAIRE, M. and ETIENNE, A., 2013. Tolerance Analysis Approach based on the Classification of Uncertainty (Aleatory/Epistemic). *Procedia CIRP*, vol. 10, no. 0, pp. 287-293 ISSN 2212-8271. DOI http://dx.doi.org/10.1016/j.procir.2013.08.044.

DAS, B., 2004. Generating conditional probabilities for Bayesian networks: Easing the knowledge acquisition problem. *ArXiv Preprint cs/0411034*.

DATTA, P.P. and ROY, R., 2010. Cost modelling techniques for availability type service support contracts: a literature review and empirical study. *CIRP Journal of Manufacturing Science and Technology*, vol. 3, no. 2, pp. 142-157.

DATTA, P.P. and ROY, R., 2013. Incentive issues in performance-based outsourcing contracts in the UK defence industry: a simulation study. *Production Planning & Control*, 04/01; 2014/04, vol. 24, no. 4-5, pp. 359-374 ISSN 0953-7287. DOI 10.1080/09537287.2011.648488.

DE BRENTANI, U., 1989. Success and failure in new industrial services. *Journal of Product Innovation Management*, vol. 6, no. 4, pp. 239-258.

DE COSTER, R., 2011. A collaborative approach to forecasting product–service systems (PSS). *The International Journal of Advanced Manufacturing Technology*, vol. 52, no. 9-12, pp. 1251-1260.

de Weck Olivier, Eckert Claudia M and JOHN, C.P., 2007. A classification of uncertainty for early product and system design. *Guidelines for a Decision Support Method Adapted to NPD Processes*.

DEAN, A.M., 2004. Links between organisational and customer variables in service delivery: Evidence, contradictions and challenges. *International Journal of Service Industry Management*, vol. 15, no. 4, pp. 332-350.

DEKKER, R., KLEIJN, M.J. and DE ROOIJ, P.J., 1998. A spare parts stocking policy based on equipment criticality. *International Journal of Production Economics*, 9/20, vol. 56–57, no. 0, pp. 69-77 ISSN 0925-5273. DOI http://dx.doi.org/10.1016/S0925-5273(97)00050-9.

DEMETER, K., BOER, H., PRIYA DATTA, P. and ROY, R., 2011. Operations strategy for the effective delivery of integrated industrial product-service offerings: two exploratory defence industry case studies. *International Journal of Operations & Production Management*, vol. 31, no. 5, pp. 579-603.

DENZIN, N.K. and LINCOLN, Y.S., 2000. The discipline and practice of qualitative research. *Handbook of Qualitative Research*, vol. 2, pp. 1-28.

DEQUECH, D., 2004. Uncertainty: individuals, institutions and technology. *Cambridge Journal of Economics*, May 01, vol. 28, no. 3, pp. 365-378 DOI 10.1093/cje/beh017.

DEVILEE, J. and KNOL, A., 2012. Software to support expert elicitation: An exploratory study of existing software packages. *RIVM Letter Report 630003001*.

DHINGRA, T., 2011. *Literature Review: Evolving variables and methodology.*MILLER, W.L. and CRABTREE, B.F., 1999. *Doing qualitative research.* Sage Publications, Incorporated.

DLAMINI, W.M., 2010. A Bayesian belief network analysis of factors influencing wildfire occurrence in Swaziland. *Environmental Modelling & Software*, 2, vol. 25, no. 2, pp. 199-208 ISSN 1364-8152. DOI http://dx.doi.org/10.1016/j.envsoft.2009.08.002.

DRURY, C.G., 2001. *Human Factors in Aircraft Maintenance*.

DRUZDZEL, M.J. and Van Der Gaag, Linda C. Elicitation of probabilities for belief networks: combining qualitative and quantitative informationAnonymous *Proceedings of the Eleventh conference on Uncertainty in artificial intelligence*, 1995.

DU, T.C., LAI, V.S., CHEUNG, W. and CUI, X., 2012. Willingness to share information in a supply chain: A partnership-data-process perspective. *Information & Management*, 3, vol. 49, no. 2, pp. 89-98 ISSN 0378-7206. DOI http://dx.doi.org/10.1016/j.im.2011.10.003.

DUBOIS, D. and FARGIER, H., 2003. *Qualitative decision rules under uncertainty.* Springer.

DURUGBO, C. and RIEDEL, J.C.K.H., 2013. Readiness assessment of collaborative networked organisations for integrated product and service delivery. *International Journal of Production Research*, 01/15; 2015/03, vol. 51, no. 2, pp. 598-613 ISSN 0020-7543. DOI 10.1080/00207543.2012.658529.

EASTERBY-SMITH, M., THORPE, R. and JACKSON, P.R., 2012. *Management research.* Sage.

EDGETT, S. and PARKINSON, S., 1993. Marketing for Service Industries-A Revie. *The Service Industries Journal*, 07/01; 2015/01, vol. 13, no. 3, pp. 19-39 ISSN 0264-2069. DOI 10.1080/02642069300000048.

EDVARDSSON, B., GUSTAFSSON, A. and ROOS, I., 2005. Service portraits in service research: a critical review. *Int J of Service Industry Mgmt*, 02/01; 2015/01, vol. 16, no. 1, pp. 107-121 ISSN 0956-4233. DOI 10.1108/09564230510587177.

EMBLEMSVÅG, J., 2003. *Life-cycle costing: using activity-based costing and Monte Carlo methods to manage future costs and risks.* Wiley.

ENDRENYI, J., ABORESHEID, S., ALLAN, R., ANDERS, G., ASGARPOOR, S., BILLINTON, R., CHOWDHURY, N., DIALYNAS, E., FIPPER, M. and FLETCHER, R., 2001. The present status of maintenance strategies and the impact of maintenance on reliability. *Power Systems, IEEE Transactions on*, vol. 16, no. 4, pp. 638-646.

EPPEN, G.D. and MARTIN, R.K., 1988. Determining safety stock in the presence of stochastic lead time and demand. *Management Science*, vol. 34, no. 11, pp. 1380-1390.

Erkoyuncu, J. A., Roy, R., Shehab, E., Wardle, P. Uncertainty challenges in service cost estimation for product- service systems in the aerospace and defence industriesAnonymous *Proceedings of the 1st CIRP IPS2 Conference*. Cranfield University, 2009.

ERKOYUNCU, J., ROY, R., SHEHAB, E.and CHERUVU, K., 2011a. *Understanding service uncertainties in industrial product-service system cost estimation.* Springer London, -02-01/, ISBN 0268-3768.

ERKOYUNCU, J.A., 2011. *'Cost uncertainty management and modelling for industrial product-service systems'. PhD Thesis.* Cranfiled University, Bedfordshire.

ERKOYUNCU, J.A., ROY, R., DATTA, P., WARDLE, P. and MURPHY, F., 2011b. Service Uncertainty and Cost for Product Service Systems. In: I. NG, G. PARRY, P. WILD, D. MCFARLANE, P. TASKER and R. ROY eds., *Complex Engineering Service Systems*Springer London, pp. 129-147 ISBN 978-0-85729-189-9.

EVANS, J.S.,. Introduction to Structured Expert Elicitation: A Risk Analysis PerspectiveAnonymous *Prepared for Methods for Research Synthesis: A Cross Disciplinary Workshop*, 2013.

FINKE, G.R. and P. HERTZ. Uncertainties in After-Sales Field Service NetworksAnonymous *Proceedings of the 2nd International Research Symposium in Service Management, Yogyakarta, Indonesia*, 2011.

FLAMING, S.C., 2007. *Leadership of risk decision making in a complex, technology organization: The deliberative decision making model.* ProQuest.

GARVEY, P.R., 2000. Probability methods for cost uncertainty analysis: A systems engineering perspective ISSN 9780824789664.

GOEBEL, M. and GRUENWALD, L., 1999. A survey of data mining and knowledge discovery software tools. *ACM SIGKDD Explorations Newsletter*, vol. 1, no. 1, pp. 20-33.

GOEDKOOP, M.J., 1999. *Product service systems, ecological and economic basics.* Ministry of Housing, Spatial Planning and the Environment, Communications Directorate.

GOH, Y.M., L. NEWNES, C. MCMAHON, A. MILEHAM and C.J. PAREDIS. A framework for considering uncertainty in quantitative life cycle cost estimationAnonymous *ASME 2009 International Design Engineering Technical Conferences and Computers and Information in Engineering Conference*, 2009.

GORDON, T.J., 1994. The delphi method. *Futures Research Methodology*, vol. 2.

Gosling, P, J,., 21 - 22 May 2013. *Introduction to expert elicitation.* Lund University, Sweden: Short Course/Workshop: Integrative Modelling- Data Synthesis and Emulation.

GROTE, G., 2009. *Management of uncertainty: theory and application in the design of systems and organizations.* Springer Science & Business Media.

GUO, L. and NG, I., 2011. The co-production of equipment-based services: An interpersonal approach. *European Management Journal*, 2, vol. 29, no. 1, pp. 43-50 ISSN 0263-2373. DOI http://dx.doi.org/10.1016/j.emj.2010.08.005.

H, J., A, B. and J, B., 2004. *Strategic Decision Making in Modern Manufacturing.* Massachusetts: Kluwer Academic Publishers.

HANEA, A. and KUROWICKA, D., 2008. Mixed non-parametric continuous and discrete Bayesian belief nets. *Advances in Mathematical Modeling for Reliability*, pp. 9.

HANEA, A.M., KUROWICKA, D. and COOKE, R.M., 2006. Hybrid method for quantifying and analyzing bayesian belief nets. *Quality and Reliability Engineering International*, vol. 22, no. 6, pp. 709-729 SCOPUS.

HANSSON, F. and SJÖKVIST , S., 2013. *Modelling expert judgement into a bayesian belief network. a method for consistent and robust determination of conditional probability tables.* Lund University.

HARRISON, A. Design for service–harmonising product design with a services strategyAnonymous *Proceedings of GT2006, ASME Turbo Expo*, 2006.

HECKERMAN, D., GEIGER, D. and CHICKERING, D., 1995. Learning Bayesian networks: The combination of knowledge and statistical data. *Machine Learning*, 09/01, vol. 20, no. 3, pp. 197-243 ISSN 0885-6125. DOI 10.1007/BF00994016.

HEGDE, G.G. and KUBAT, P., 1989. Diagnostics design: A product support strategy. *European Journal of Operational Research*, 1/5, vol. 38, no. 1, pp. 35-43 ISSN 0377-2217. DOI 10.1016/0377-2217(89)90466-9.

HENRIKSEN, H.J. and BARLEBO, H.C., 2008. Reflections on the use of Bayesian belief networks for adaptive management. *Journal of Environmental Management*, vol. 88, no. 4, pp. 1025-1036.

HILL, A. and CUTHBERTSON, R., 2011. Fitness map: a classification of internal strategic fit in service organisations. *International Journal of Operations & Production Management*, vol. 31, no. 9, pp. 991-1021 ISSN 0144-3577. DOI 10.1108/01443571111165857.

HL, C.M.L., 1990. Out of touch with customer needs? Spare parts and after sales service. *Sloan Management Review*, vol. 31, no. 2, pp. 55-66.

HO, Y. and H. WANG. Applying fuzzy Delphi method to select the variables of a sustainable urban system dynamics modelAnonymous *Proceedings of the 26th International Conference of System. http://www. systemdynamics. org/conferences/2008/proceed/(accessed on 15/May/2011).[Links]*, 2008.

HOBBS, A., AVERS, K.B. and HILES, J.J., 2011. *Fatigue Risk Management in Aviation Maintenance: Current Best Practices and Potential Future Countermeasures*.

HOCKLEY, C. and PHILLIPS, P., 2012. The impact of no fault found on through-life engineering services. *Journal of Quality in Maintenance Engineering*, vol. 18, no. 2, pp. 141-153 ISSN 1355-2511. DOI 10.1108/13552511211244184.

HOCKLEY, C.J., SMITH, J.C. and LACEY, L.J., 2011. Contracting for availability and capability in the defence environment. In: *Complex Engineering Service Systems*Springer, pp. 237-256.

HORA, S., 2007. 8 Eliciting Probabilities from Experts. *Advances in Decision Analysis: From Foundations to Applications*, pp. 129.

HORA, S.C., HORA, J.A. and DODD, N.G., 1992. Assessment of probability distributions for continuous random variables: A comparison of the bisection and fixed value methods. *Organizational Behavior and Human Decision Processes*, vol. 51, no. 1, pp. 133-155.

Hu Xiao-xuan, Wang Hui and Wang Shuo. Using Expert's Knowledge to Build Bayesian NetworksAnonymous *Computational Intelligence and Security Workshops, 2007. CISW 2007. International Conference on*, 2007.

HUISKONEN, J., 2001. Maintenance spare parts logistics: Special characteristics and strategic choices. *International Journal of Production Economics*, 5/6, vol. 71, no. 1–3, pp. 125-133 ISSN 0925-5273. DOI http://dx.doi.org/10.1016/S0925-5273(00)00112-2.

HUNTER, H., 1997. *Depot Maintenance Capacity and Utilization Measurement Handbook*.

JANKAUSKAS, L. and S. MCLAFFERTY. BestFit, distribution-fitting software by Palisade CorporationAnonymous *Proceedings of the 28th conference on Winter simulation*, 1996.

JANZ, D., S. SCHNEIDER, M. KEMPF and E. WESTKAMPER. Bayesian nets for life cycle cost forecastingAnonymous *Proceedings of the 13th CIRP international conference on life cycle engineering, Leuven*, 2006.

JENKINSON, D., 2005. The elicitation of probabilities: A review of the statistical literature.

JENSEN, F.V., 1996. *An introduction to Bayesian networks.* UCL press London.

JENSSEN, T., LÆGREID, A., KOMOROWSKI, J. and HOVIG, E., 2001. A literature network of human genes for high-throughput analysis of gene expression. *Nature Genetics*, vol. 28, no. 1, pp. 21-28.

JOHANSSON, C. and ERICSON, Å., 2011. Visualization of knowledge maturity for product-service system development. In: Amaresh Chakrabarti ed., *Research into Design*,Research Publishing Services, pp. 312-319 ISBN 978-981-08-7721-7.

JOHN, A.E., ROY, R., SHEHAB, E. and KUTSCH, E., 2014. An innovative uncertainty management framework to support contracting for product-service availability. *Journal of Service Management*, 10/14; 2014/12, vol. 25, no. 5, pp. 603-638 ISSN 1757-5818. DOI 10.1108/JOSM-07-2013-0193.

JOHNSEN, T., HOWARD, M. and MIEMCZYK, J., 2009. UK defence change and the impact on supply relationships. *Supp Chain Mnagmnt*, 06/19; 2015/03, vol. 14, no. 4, pp. 270-279 ISSN 1359-8546. DOI 10.1108/13598540910970108.

JONAS, W., MORELLI, N. and MÜNCH, J., 2009. Designing a product service system in a social framework: methodological and ethical considerations.

KAPLAN, S. and GARRICK, B.J., 1981. On The Quantitative Definition of Risk. *Risk Analysis*, vol. 1, no. 1, pp. 11-27 ISSN 1539-6924. DOI 10.1111/j.1539-6924.1981.tb01350.x.

KAPLETIA, D. and PROBERT, D., 2010. Migrating from products to solutions: An exploration of system support in the UK defense industry. *Industrial Marketing Management*, vol. 39, no. 4, pp. 582-592.

KAPLETIA, D. and PROBERT, D., 2010. Migrating from products to solutions: An exploration of system support in the UK defense industry. *Industrial Marketing Management*, vol. 39, no. 4, pp. 582-592.

KARIAN, Z.A., 2010. *Handbook of fitting statistical distributions with R.* CRC Press.

KEMP-BENEDICT, E., 2008. Elicitation Techniques for Bayesian Network Models.

KEMP-BENEDICT, E., BHARWANI, S., DE LA ROSA, E., KRITTASUDTHACHEEWA, C. and MATIN, N., 2009. *Assessing Water-Related Poverty using the Sustainable Livelihoods Framework*.

KENNEDY, W., WAYNE PATTERSON, J. and FREDENDALL, L.D., 2002. An overview of recent literature on spare parts inventories. *International Journal of Production Economics*, vol. 76, no. 2, pp. 201-215.

KENNETT, R.J., KORB, K.B. and NICHOLSON, A.E., 2001. Seabreeze prediction using Bayesian networks. In: *Advances in Knowledge Discovery and Data Mining*Springer, pp. 148-153.

KHOO, L., 1999. An IDEF0 model-based intelligent fault diagnosis system for manufacturing systems. *International Journal of Production Research*, vol. 37, no. 1, pp. 35-48.

KHUMBOON, R., KARA, S. and IBBOTSON, S., 2011. A Simplified Decision Making Model for Employing Product Service System in Industry at a Preliminary Planning Stage, pp. 177-182 ISSN 978-3-642-19688-1. DOI 10.1007/978-3-642-19689-8_32.

KINNISON, H.A. and SIDDIQUI, T., 2012. *Aviation maintenance management.*

KNIGHT, F.H., 1921. *Risk, uncertainty and profit*, Boston; New York: Houghton Mifflin Company /z-wcorg/.

KNOL, A.B., SLOTTJE, P., VAN DER SLUIJS, J.P. and LEBRET, E., 2010. The use of expert elicitation in environmental health impact assessment: a seven step procedure. *Environmental Health : A Global Access Science Source*, 20100426, Apr 26, vol. 9, pp. 19-069X-9-19 ISSN 1476-069X; 1476-069X. DOI 10.1186/1476-069X-9-19 [doi].

KOEHLER, J.J., 1996. The base rate fallacy reconsidered: Descriptive, normative, and methodological challenges. *Behavioral and Brain Sciences*, vol. 19, no. 01, pp. 1-17 DOI 10.1017/S0140525X00041157.

KOMONEN, K., 2002. A cost model of industrial maintenance for profitability analysis and benchmarking. *International Journal of Production Economics*, vol. 79, no. 1, pp. 15-31.

KORB, K.B. and NICHOLSON, A.E., 2003. *Bayesian artificial intelligence.* cRc Press.

KORB, K.B. and NICHOLSON, A.E., 2010. *Bayesian artificial intelligence.* cRc Press.

KOTHARI, C., 2009. *Research methodology: methods and techniques.* New Age International.

KRAGT, M.E., University of Tasmania. Landscape Logic, Australia. Department of the Environment, Water,Heritage, and the Arts., 2009. *A Beginners Guide to Bayesian Network Modelling for Integrated Catchment Management.* Landscape Logic.

KRATZ, L., 2001. Achieving Logistics Excellence through Performance-Based Logistics. *Logistics Spectrum*, vol. 35, pp. 3.

KREYE, M., L. NEWNES and Y. GOH. Uncertainty analysis and its application to service contracts *ASME 2011 International Design Engineering Technical Conferences & Computers and Information in Engineering Conference IDETC/CIE 2011*. Washington, DC, USA, 2011a.

KREYE, M., Y. GOH and L. NEWNES. Manifestation of uncertainty - A classification *International Conference on Engineering Design, ICED11*. DTU Copenhagen, Copenhagen, Denmark, 2011b.

KREYE, M.E., 2011. *Uncertainty analysis in competitive bidding for service contracts.* University of Bath.

KREYE, M.E., Y.M. GOH and L.B. NEWNES. Modelling Uncertainty in Competitive Bidding *ASME 2012 International Design Engineering Technical Conferences and Computers and Information in Engineering Conference*, 2012.

KUO, T.C. and WANG, M.L., 2012. The optimisation of maintenance service levels to support the product service system. *International Journal of Production Research*, 12/01; 2014/04, vol. 50, no. 23, pp. 6691-6708 ISSN 0020-7543. DOI 10.1080/00207543.2011.616916.

KUROWICKA, D. and COOKE, R.M., 2006. *Uncertainty analysis with high dimensional dependence modelling.* John Wiley & Sons.

LAGEMANN, H. and MEIER, H., 2014. Robust Capacity Planning for the Delivery of Industrial Product-service Systems. *Procedia CIRP*, vol. 19, no. 0, pp. 99-104 ISSN 2212-8271. DOI http://dx.doi.org/10.1016/j.procir.2014.05.021.

LANGFORD, E., 2006. *Quartiles in elementary statistics. Journal of Statistics Education*.

LASZLO, A. and KRIPPNER, S., 1998. Systems Theories: Their origins, foundations, and development. *Advances in Psychology-Amsterdam-*, vol. 126, pp. 47-76.

LEACHMAN, R.C., 1997. Closed-loop measurement of equipment efficiency and equipment capacity. *Semiconductor Manufacturing, IEEE Transactions on*, vol. 10, no. 1, pp. 84-97 ISSN 0894-6507.

Lecture 3: Building Bayesian networks , 2013.: Dept. Model-Based System Development, ICIS, Radboud University [viewed Jan 2013]. Available from: http://cs.ru.nl/~marinav/Teaching/BDMinAI/.

LEE, H. and WHANG, S., 1999. Decentralized multi-echelon supply chains: Incentives and information. *Management Science*, vol. 45, no. 5, pp. 633-640.

LEWIS, M.A. and ROEHRICH, J.K., 2009. Contracts, relationships and integration: towards a model of the procurement of complex performance. *International Journal of Procurement Management*, vol. 2, no. 2, pp. 125-142.

LI, X. and Z.G. LIU. An evolution framework of product service system for firms across service supply chains with integrated lifecycle perspectiveAnonymous *Logistics Systems and Intelligent Management, 2010 International Conference on*, 2010.

LIAO, C. and SHYU, C., 1993. An Analytical Determination of Lead Time with Normal Demand. *International Journal of Operations & Production Management*, vol. 11, no. 9, pp. 72-78 ISSN 0144-3577. DOI 10.1108/EUM0000000001287.

LIMA JUNIOR, F.R., OSIRO, L. and CARPINETTI, L.C.R., 2014. A comparison between Fuzzy AHP and Fuzzy TOPSIS methods to supplier selection. *Applied Soft Computing*, 8, vol. 21, no. 0, pp. 194-209 ISSN 1568-4946. DOI

Linstone, H. A., and Turoff , M., 1975. The Delphi Method.

LOCKETT, H., JOHNSON, M., EVANS, S. and BASTL, M., 2011. Product Service Systems and supply network relationships: an exploratory case study. *Journal of Manufacturing Technology Management*, vol. 22, no. 3, pp. 293-313.

LOVELOCK, C.H., 1984. Strategies for managing demand in capacity-constrained service organisations. *Service Industries Journal*, vol. 4, no. 3, pp. 12-30.

LOVELOCK, C.H., 1999. Developing marketing strategies for transnational service operations. *Journal of Services Marketing*, vol. 13, no. 4/5, pp. 278-295.

LOVERIDGE, D., 2004. Experts and foresight: review and experience. *International Journal of Foresight and Innovation Policy*, vol. 1, no. 1, pp. 33-69.

LUNSFORD, B.R., 1993. Methodology: Variables and Levels of Measurement. *JPO: Journal of Prosthetics and Orthotics*, vol. 5, no. 4 ISSN 1040-8800.

LUXHØJ, J.T., RIIS, J.O. and THORSTEINSSON, U., 1997. Trends and perspectives in industrial maintenance management. *Journal of Manufacturing Systems*, vol. 16, no. 6, pp. 437-453.

MACAL, C.M. and NORTH, M.J., 2010. Tutorial on agent-based modelling and simulation. *J of Sim*, print, vol. 4, no. 3, pp. 151-162 ISSN 1747-7778.

MAHJOUB, M.A. and KALTI, K., 2011. Software comparison dealing with bayesian networks. In: *Advances in Neural Networks–ISNN 2011*Springer, pp. 168-177.

MANZINI, E. and VEZZOLI, C., 2003. A strategic design approach to develop sustainable product service systems: examples taken from the 'environmentally friendly innovation'Italian prize. *Journal of Cleaner Production*, vol. 11, no. 8, pp. 851-857.

MARCOT, B.G., 2006. Characterizing species at risk I: modeling rare species under the Northwest Forest Plan. *Ecology and Society*, vol. 11, no. 2, pp. 10.

MARCOT, B.G., STEVENTON, J.D., SUTHERLAND, G.D. and MCCANN, R.K., 2006. Guidelines for developing and updating Bayesian belief networks applied to ecological modeling and conservation. *Canadian Journal of Forest Research*, 12/01; 2014/09, vol. 36, no. 12, pp. 3063-3074 ISSN 0045-5067. DOI 10.1139/x06-135.

MÁRQUEZ, A.C., 2007. *The maintenance management framework: models and methods for complex systems maintenance.* Springer Science & Business Media.

MARTINEZ, V., BASTL, M., KINGSTON, J. and EVANS, S., 2010. Challenges in transforming manufacturing organisations into product-service providers. *Journal of Manufacturing Technology Management*, vol. 21, no. 4, pp. 449-469 ISSN 1741-038X.

MASKERY, S.M., HU, H., HOOKE, J., SHRIVER, C.D. and LIEBMAN, M.N., 2008. A Bayesian derived network of breast pathology co-occurrence. *Journal of Biomedical Informatics*, 4, vol. 41, no. 2, pp. 242-250 ISSN 1532-0464. DOI http://dx.doi.org/10.1016/j.jbi.2007.12.005.

MATAMOROS, M.O., F.M. CADENA, T.R. PADILLA and L.I. REYES. After-Sales Service Parts Supply Chain System in OEM Telecommunication FirmsAnonymous *Proceedings of the 52nd Annual Meeting of the ISSS*, 2008.

MATHE, H. and SHAPIRO, R.D., 1993. *Integrating service strategy in the manufacturing company.* Chapman & Hall.

MATHIAK, B. and S. ECKSTEIN. Five steps to text mining in biomedical literatureAnonymous *Proceedings of the second European workshop on data mining and text mining in bioinformatics*, 2004.

MATTILA, A.S. and RO, H., 2008. Customer satisfaction, service failure, and service recovery. *Handbook of Hospitality Marketing Management*, pp. 297-323.

MATZEN D., A.M.M. Opportunity parameters for the development of Product/Service System MARJANOVIC, D., ed. *Proceedings of the 9th International Design Conference DESIGN 2006*, 2006.

MCMAHON, C. and BALL, A., 2013. Information Systems Challenges for through-life Engineering. *Procedia CIRP*, vol. 11, no. 0, pp. 1-7 ISSN 2212-8271. DOI http://dx.doi.org/10.1016/j.procir.2013.07.071.

MCMANUS, D. and HASTINGS, P., 2005. A framework for understanding uncertainty and its mitigation and exploitation in complex systems.

MCNAUGHT, K.R. and ZAGORECKI, A.T., 2011. Modelling techniques to support the adoption of predictive maintenance. In: *Complex Engineering Service Systems*Springer, pp. 277-296.

MEIER, H. and B. FUNKE. Resource Planning of Industrial Product-Service Systems (IPS²) by a Heuristic Resource Planning ApproachAnonymous *Industrial Product-Service Systems (IPS²), Proceedings of the 2nd CIRP IPS² Conference*, *Linköping University*, *Linköping*, 2010.

MEIER, H., ROY, R. and SELIGER, G., 2010. Industrial Product-Service Systems—IPS2. *CIRP Annals - Manufacturing Technology*, vol. 59, no. 2, pp. 607-627 ISSN 0007-8506.

MEIJER, I.S.M., HEKKERT, M.P., FABER, J. and SMITS, R.E.H.M., 2006. Perceived uncertainties regarding socio-technological transformations: towards a framework. *International Journal of Foresight and Innovation Policy*, 01/01, vol. 2, no. 2, pp. 214-240.

MERKHOFER, M.W., 1975. Flexibility and Decision Analysis.

MJEMA, E., 2002. An analysis of personnel capacity requirement in the maintenance department by using a simulation method. *Journal of Quality in Maintenance Engineering*, vol. 8, no. 3, pp. 253-273.

MO, J., 2012. Performance Assessment of Product Service System from System Architecture Perspectives. *Advances in Decision Sciences*, vol. 2012.

MONT, O., 2001. *Introducing and developing a Product-Service System (PSS) concept in Sweden.* ISBN 1650-1675.

MONT, O., 2004. *Product-service systems: Panacea or myth?* IIIEE, Lund University; Lund University ISBN 91-88902-33-1; 1402-3016.

MONT, O.K., 2002. Clarifying the concept of product–service system. *Journal of Cleaner Production*, 6, vol. 10, no. 3, pp. 237-245 ISSN 0959-6526. DOI http://dx.doi.org/10.1016/S0959-6526(01)00039-7.

MORALES NÁPOLES, O., 2010. Bayesian belief nets and vines in aviation safety and other applications.

MORALES, O., KUROWICKA, D. and ROELEN, A., 2008. Eliciting conditional and unconditional rank correlations from conditional probabilities. *Reliability Engineering & System Safety*, 5, vol. 93, no. 5, pp. 699-710 ISSN 0951-8320. DOI http://dx.doi.org/10.1016/j.ress.2007.03.020.

MORELLI, N., 2002. Designing Product/Service Systems: A Methodological Exploration. *Design Issues*, Summer, vol. 18, no. 3, pp. 3-17 ISSN 07479360.

MORGAN, M.G. and HENRION, M., 1990. Uncertainty: a Guide to dealing with uncertainty in quantitative risk and policy analysis Cambridge University Press. *New York, New York, USA*.

MORRIS, D.E., OAKLEY, J.E. and CROWE, J.A., 2014. A web-based tool for eliciting probability distributions from experts. *Environmental Modelling & Software*, 2, vol. 52, no. 0, pp. 1-4 ISSN 1364-8152. DOI http://dx.doi.org/10.1016/j.envsoft.2013.10.010.

MULDER, W., R.J. BASTEN, J.M. JAUREGUI BECKER and v.L. DONGEN. Towards structured integration of maintenance knowledge in industrial equipment designAnonymous , 2013.

MURRAY, J., 1961. *The Oxford English Dictionary, ,* Vol. XI, ed. Oxford, United Kingdom: Clarendon Press.

MURRAY, K. and SCHLACTER, J., 1990. The impact of services versus goods on consumersâ€™ assessment of perceived risk and variability. *Journal of the Academy of Marketing Science*, 12/01, vol. 18, no. 1, pp. 51-65 ISSN 0092-0703. DOI 10.1007/BF02729762.

NEELY, A., 2008. Exploring the financial consequences of the servitization of manufacturing. *Operations Management Research*, vol. 1, no. 2, pp. 103-118 ISSN 1936-9735.

NEIL, M., FENTON, N. and NIELSON, L., 2000. Building large-scale Bayesian networks. *The Knowledge Engineering Review*, vol. 15, no. 03, pp. 257-284.

NEIL, M., TAILOR, M., MARQUEZ, D., FENTON, N. and HEARTY, P., 2008. Modelling dependable systems using hybrid Bayesian networks. *Reliability Engineering & System Safety*, 7, vol. 93, no. 7, pp. 933-939 ISSN 0951-8320. DOI http://dx.doi.org/10.1016/j.ress.2007.03.009.

NEŠLEHOVÁ, J., 2007. On rank correlation measures for non-continuous random variables. *Journal of Multivariate Analysis*, vol. 98, no. 3, pp. 544-567.

NG, I. and N. YIP. Identifying risk and its impact on contracting through a benefit based-model framework in business to business contracting: case of the defence industryAnonymous *Proceedings of the 19th CIRP design Conference–Competitive design*, 2009.

NG, I., PARRY, G., MCFARLANE, D. and TASKER, P., 2011. Towards a core integrative framework for complex engineering service systems. In: *Complex Engineering Service Systems*Springer, pp. 1-19.

NG, I.C., L. GUO, J. SCOTT and N.K. YIP. Towards a benefit-based framework for understanding business to business services and its impact on contract and capabilityAnonymous *10th International Research Seminar in Services Management: Marketing, Strategy, Economics, Operations & Human Resources: Insights into Service Activities La Londe, France*, 2008.

NG, I.C., MAULL, R. and YIP, N., 2009. Outcome-based contracts as a driver for systems thinking and service-dominant logic in service science: Evidence from the defence industry. *European Management Journal*, vol. 27, no. 6, pp. 377-387.

NIKOVSKI, D., 2000. Constructing Bayesian networks for medical diagnosis from incomplete and partially correct statistics. *Knowledge and Data Engineering, IEEE Transactions on*, vol. 12, no. 4, pp. 509-516.

NOOR, K.B.M., 2008. Case study: a strategic research methodology. *American Journal of Applied Sciences*, vol. 5, no. 11, pp. 1602-1604.

NOWICKI, D., KUMAR, U.D., STEUDEL, H.J. and VERMA, D., 2008. Spares Provisioning under Performance-Based Logistics Contract: Profit-Centric Approach. *The Journal of the Operational Research Society*, Mar., vol. 59, no. 3, pp. 342-352 ISSN 01605682.

NOWICKI, D., W.S. RANDALL and A. GOROD. A framework for performance based logistics: A system of systems approachAnonymous *Ultra Modern Telecommunications and Control Systems and Workshops (ICUMT), 2010 International Congress on*, 2010.

Oakley J. E. and O'Hagan, A., 2010. *SHELF: the Sheffield Elicitation Framework (version 2.0).* School of Mathematics and Statistics, University of Sheffield, UK.: .

OAKLEY, J.E. and O'HAGAN, A., 2007. Uncertainty in prior elicitations: a nonparametric approach. *Biometrika*, vol. 94, no. 2, pp. 427-441.

Oberkampf, W. L., Helton, J. C., Joslyn, C. A., Wojtkiewicz, S. F., and Ferson, S., 2004. Challenge Problems: Uncertainty in System Response Given Uncertain Parameters. *Reliab Engng Syst Safety*, vol. 85, pp. 11–19.

OBERKAMPF, W.L. and ROY, C.J., 2010. *Verification and validation in scientific computing.* Cambridge University Press.

O'Hagan, A., Buck, C.E., Daneshkhah, A., Eiser, R., Garthwaite, P, H., Jenkinson, D,J., Oakley, E., Rakow, T., 2006. *Uncertain Judgements: Eliciting Experts' Probabilities.* Wiley ISBN 9780470029992.

O'Hagan, A., Buck, C.E., Daneshkhah, A., Eiser, R., Garthwaite, P, H., Jenkinson, D,J., Oakley, E., Rakow, T., 2006. *Uncertain Judgements: Eliciting Experts' Probabilities.* Wiley ISBN 9780470029992.

OLIVA, R. and KALLENBERG, R., 2003. Managing the transition from products to services. *International Journal of Service Industry Management*, vol. 14, no. 2, pp. 160-172 ISSN 0956-4233.

OLORUNNIWO, F., HSU, M.K. and UDO, G.J., 2006. Service quality, customer satisfaction, and behavioral intentions in the service factory. *Journal of Services Marketing*, vol. 20, no. 1, pp. 59-72 ISSN 0887-6045.

ORMEROD, R.J., 2010. Rational inference: deductive, inductive and probabilistic thinking. *The Journal of the Operational Research Society*, print, vol. 61, no. 8, pp. 1207-1223 ISSN 0160-5682.

OWENS, J., S. MILLER and D. DEANS. Availability optimization using spares modeling and the six sigma processAnonymous *Reliability and Maintainability Symposium, 2006. RAMS '06. Annual*, 2006.

OYEBISI, T., 2000. On reliability and maintenance management of electronic equipment in the tropics. *Technovation*, vol. 20, no. 9, pp. 517-522.

PARAKHINE, A., T. O'NEILL and J. LEANEY. Application of Bayesian Networks to Architectural OptimisationAnonymous *Engineering of Computer-Based Systems, 2007. ECBS '07. 14th Annual IEEE International Conference and Workshops on the*, 2007.

PARIDA, V., RÖNNBERG-SJÖDIN, D., WINCET, J. and YLINENPÄÄ, H., 2013. Win-win Collaboration, Functional Product Challenges and Value-chain Delivery: A Case Study Approach. *Procedia CIRP*, vol. 11, no. 0, pp. 86-91 ISSN 2212-8271.

PARK, H. and CHO, S., 2012. A modular design of Bayesian networks using expert knowledge: Context-aware home service robot. *Expert Systems with Applications*, vol. 39, no. 3, pp. 2629-2642.

Parlier, H, Greg,., 2005. *Transforming U.S. Army Logistics: A Strategic “Supply Chain” Approach for Inventory Management.* Association Of the United States Army.

PAZ, N.M. and LEIGH, W., 1994. Maintenance scheduling: issues, results and research needs. *International Journal of Operations & Production Management*, vol. 14, no. 8, pp. 47-69.

PEARL, J., 1988. *Probabilistic reasoning in intelligent systems: networks of plausible inference.* Morgan Kaufmann.

PELTZ, E., 2004. *The Effects of Equipment Age on Mission Critical Failure Rates: A Study of M1 Tanks.* Rand Corporation.

PETERSON, C. and MILLER, A., 1964. Mode, median, and mean as optimal strategies. *Journal of Experimental Psychology*, vol. 68, no. 4, pp. 363.

PFEFFER, J. and SALANCIK, G.R., 2003. *The external control of organizations: A resource dependence perspective.* Stanford University Press.

PHUMBUA, S. and TJAHJONO, B., 2010. Simulation Modelling of Product-Service Systems: the Missing Link. In: S. HINDUJA and L. LI eds., Springer London,01/01, pp. 135-138 ISBN 978-1-84996-431-9. DOI 10.1007/978-1-84996-432-6_31.

PHUMBUA, S. and TJAHJONO, B., 2012. Towards product-service systems modelling: a quest for dynamic behaviour and model parameters. *International Journal of Production Research*, vol. 50, no. 2, pp. 425-442.

PINTELON, L.M. and GELDERS, L.F., 1992. Maintenance management decision making. *European Journal of Operational Research*, 5/11, vol. 58, no. 3, pp. 301-317 ISSN 0377-2217. DOI http://dx.doi.org/10.1016/0377-2217(92)90062-E.

PITCHFORTH, J. and MENGERSEN, K., 2013. A proposed validation framework for expert elicited Bayesian Networks. *Expert Systems with Applications*, vol. 40, no. 1, pp. 162-167.

POLLINO, C.A., WOODBERRY, O., NICHOLSON, A., KORB, K. and HART, B.T., 2007. Parameterisation and evaluation of a Bayesian network for use in an ecological risk assessment. *Environmental Modelling & Software*, 8, vol. 22, no. 8, pp. 1140-1152 ISSN 1364-8152. DOI http://dx.doi.org/10.1016/j.envsoft.2006.03.006.

PRADHAN, M., G. PROVAN, B. MIDDLETON and M. HENRION. Knowledge engineering for large belief networksAnonymous *Proceedings of the Tenth international conference on Uncertainty in artificial intelligence*, 1994.

PRICE, P.C., 1998. Effects of a Relative-Frequency Elicitation Question on Likelihood Judgment Accuracy: The Case of External Correspondence. *Organizational Behavior and Human Decision Processes*, 12, vol. 76, no. 3, pp. 277-297 ISSN 0749-5978. DOI http://dx.doi.org/10.1006/obhd.1998.2807.

Qingwei Yang, Naichao Wang, Ma Lin and Li Lei. Optimization of spare parts based on inventory level and turnaround timeAnonymous *Reliability, Maintainability and Safety (ICRMS), 2011 9th International Conference on*, 2011.

RABETINO, R., KOHTAMÄKI, M., LEHTONEN, H. and KOSTAMA, H., 2015. Developing the concept of life-cycle service offering. *Industrial Marketing Management*.

RAGHURAM, S., XIA, Y., GE, J., PALAKAL, M., JONES, J., PECENKA, D., TINSLEY, E., BANDOS, J. and GEESAMAN, J., 2011. AutoBayesian: Developing Bayesian Networks Based on Text Mining, vol. 6588, pp. 450-453 ISSN 978-3-642-20151-6. DOI 10.1007/978-3-642-20152-3_37.

RAMACHANDRAN, S. and MOONEY, R.J., 1998. *Theory refinement of bayesian networks with hidden variables*. PhD Thesis ed. Austin: University of Texas.

RANDALL, W.S., POHLEN, T.L. and HANNA, J.B., 2010. EVOLVING A THEORY OF PERFORMANCE-BASED LOGISTICS USING INSIGHTS FROM SERVICE DOMINANT LOGIC. *Journal of Business Logistics*, vol. 31, no. 2, pp. 35-61 ISSN 2158-1592. DOI 10.1002/j.2158-1592.2010.tb00142.x.

RAVINDER, H.V., KLEINMUNTZ, D.N. and DYER, J.S., 1988. The reliability of subjective probabilities obtained through decomposition. *Management Science*, vol. 34, no. 2, pp. 186-199.

REFSGAARD, J.C., van der Sluijs, Jeroen P, HØJBERG, A.L. and VANROLLEGHEM, P.A., 2007. Uncertainty in the environmental modelling process–a framework and guidance. *Environmental Modelling & Software*, vol. 22, no. 11, pp. 1543-1556.

RENOOIJ, S. and WITTEMAN, C., 1999. Talking probabilities: communicating probabilistic information with words and numbers. *International Journal of Approximate Reasoning*, vol. 22, no. 3, pp. 169-194.

RENOOIJ, S., 2001. Probability elicitation for belief networks: issues to consider. *The Knowledge Engineering Review*, vol. 16, no. 03, pp. 255-269.

RIEVLEY, J.,D. Performance-Based Launch Services Contracts: Better, Master, Cheaper?Anonymous *Proceeding of 38th Space Congress*, 2001.

RIPLEY, T. 2005. DLO Rolls Out its Efficiency Initiatives fane's. *Defense Weekly*, 19.

ROMERO ROJO, F.J., R. ROY, E. SHEHAB and P. WARDLE. Obsolescence challenges for product-service systems in aerospace and defence industryAnonymous *Proceedings of the 19th CIRP Design Conference–Competitive Design*, 2009.

ROY, C.J. and OBERKAMPF, W.L., 2011. A comprehensive framework for verification, validation, and uncertainty quantification in scientific computing. *Computer Methods in Applied Mechanics and Engineering*, 6/15, vol. 200, no. 25–28, pp. 2131-2144 ISSN 0045-7825. DOI http://dx.doi.org/10.1016/j.cma.2011.03.016.

ROY, R. and CHERUVU, K.S., 2009. A competitive framework for industrial product-service systems. *International Journal of Internet Manufacturing and Services*, 01/01, vol. 2, no. 1, pp. 4-29 DOI 10.1504/IJIMS.2009.031337.

ROY, R. and ERKOYUNCU, J.A., 2011. Service cost estimation challenges in industrial product-service systems. In: *Functional Thinking for Value Creation*Springer, pp. 1-10.

ROY, R., 2011. Delivering Service Contracts. *Complex Engineering Service Systems: Concepts and Research*, pp. 105.

RUSSO, J.E. and SCHOEMAKER, P.J., 1992. Managing overconfidence. *Sloan Management Review*, vol. 33, no. 2, pp. 7-17.

SAATY, T.L., 1977. A scaling method for priorities in hierarchical structures. *Journal of Mathematical Psychology*, 6, vol. 15, no. 3, pp. 234-281 ISSN 0022-2496. DOI http://dx.doi.org/10.1016/0022-2496(77)90033-5.

SADEK, T. and KÖSTER, M., 2011. Analyzing the practical usability of the heterogeneous modeling approach for conceptual product-service system development. In: *Functional Thinking for Value Creation*Springer, pp. 135-140.

SAGASTI, F.R. and MITROFF, I.I., 1973. Operations research from the viewpoint of general systems theory. *Omega*, 12, vol. 1, no. 6, pp. 695-709 ISSN 0305-0483. DOI http://dx.doi.org/10.1016/0305-0483(73)90087-X.

SAMSON, S., RENEKE, J.A. and WIECEK, M.M., 2009. A review of different perspectives on uncertainty and risk and an alternative modeling paradigm. *Reliability Engineering & System Safety*, 2, vol. 94, no. 2, pp. 558-567 ISSN 0951-8320. DOI DOI: 10.1016/j.ress.2008.06.004.

SANDBORN, P.A. and WILKINSON, C., 2007. A maintenance planning and business case development model for the application of prognostics and health management (PHM) to electronic systems. *Microelectronics Reliability*, vol. 47, no. 12, pp. 1889-1901.

Sasser, W, E,. 1976, November-December. Match Supply and Demand in Service Industries. *Harvard Business Review*.

SASSER, W.E., OLSEN, R.P., WYCKOFF, D.D. and Harvard University. Graduate School of Business Administration., 1978. *Management of service operations: text, cases, and readings.* Allyn and Bacon ISBN 9780205061044.

Senior Seismic Hazard Analysis Committee (SSHAC). (1997) Recommendations for probabilistic seismic hazard analysis-guidance on uncertainty and use of experts. U.S. Nuclear Regulatory Commission NUREG/CR-6327.

SHELTON, R., 2009. INTEGRATING PRODUCT AND SERVICE INNOVATION. *Research Technology Management*, vol. 52, no. 3, pp. 38.

SHIMADA, S., TAIRA, K., HARA, T. and ARAI, T., 2011. Customersâ€™ Satisfaction on Estimates of Queue Waiting Time in Service Delivery. In: J. HESSELBACH and C. HERRMANN eds., Springer Berlin Heidelberg,01/01, pp. 266-271 ISBN 978-3-642-19688-1. DOI 10.1007/978-3-642-19689-8_47.

SOANES, C., 2005. *The Oxford English Dictionary*. Oxford, UK: Oxford University Press.

SOLS, A., NOWICK, D. and VERMA, D., 2007. Defining the Fundamental Framework of an Effective Performance-Based Logistics (PBL) Contract. *Engineering Management Journal*, vol. 19, no. 2.

SOTI, R. and H. HABING. Asset Management: A Life Cycle Costing Approach: a framework for an integrated life cycle modelBREUGEL, K.V., YE, G., and YUAN, Y., eds. *2nd International Symposium on Service Life Design for Infrastructures*. http://www.crow.nl/nl/Binaries/PDF/PDF-Infradagen/20_Sot.pdf, 2010.

SPETZLER, C.S. and Stael von Holstein, Carl-Axel S, 1975. Exceptional Paper-Probability Encoding in Decision Analysis. *Management Science*, vol. 22, no. 3, pp. 340-358.

SPIEGELHALTER, D.J., DAWID, A.P., LAURITZEN, S.L. and COWELL, R.G., 1993. Bayesian analysis in expert systems. *Statistical Science*, pp. 219-247.

SPOHN, W., 1990. Direct and indirect causes. *Topoi*, 09/01, vol. 9, no. 2, pp. 125-145 ISSN 0167-7411. DOI 10.1007/BF00135893.

Srivastava, A. & Thomson, S. B., 2009. Framework Analysis: A Qualitative Methodology for Applied Policy Research. *Joaag*, vol. Vol. 4, no. No. 2.

Stael von Holstein, Cari-Axel S and MATHESON, J.E., 1978. A Manual for Encoding Probability Distributions.

STAPLEY, B.J. and G. BENOIT. Biobibliometrics: information retrieval and visualization from co-occurrences of gene names in Medline abstractsAnonymous *Pac Symp Biocomput*, 2000.

STEVEN, M. and A. RICHTER. Hierarchical planning for industrial product service systemsAnonymous *Proceeding of the 2nd CIRP IPS² conference*, 2010.

STREMERSCH, S., WUYTS, S. and FRAMBACH, R., 2001. The Purchasing of Full-Service Contracts:: An Exploratory Study within the Industrial Maintenance Market. *Industrial Marketing Management*, 1, vol. 30, no. 1, pp. 1-12 ISSN 0019-8501. DOI 10.1016/S0019-8501(99)00090-5.

SUNDIN, E., 2009. Life-Cycle Perspectives of Product/Service-Systems: In Design Theory. In: T. SAKAO and M. LINDAHL eds., Springer London,01/01, pp. 31-49 ISBN 978-1-84882-908-4. DOI 10.1007/978-1-84882-909-1_2.

SWAMIDASS, P.M. and NEWELL, W.T., 1987. Manufacturing strategy, environmental uncertainty and performance: a path analytic model. *Management Science*, vol. 33, no. 4, pp. 509-524.

TAY, A.S. and WALLIS, K.F., 2000. Density forecasting: a survey. *Journal of Forecasting*, vol. 19, no. 4, pp. 235-254.

THENENT, N.E., 2014. *The Representation of an Advanced Service delivered by a Product Service System: A Qualitative Model of Avionics Availability.*

THOMPSON, J., 1967. *Organizations in action.*

THORSTEINSSON, U., 1995. *Importance of Maintenance.* Technical University of Denmark: Denmark: Institute of Production Management and Industrial Engineering.

THUNNISSEN, D.P. Uncertainty classification for the design and development of complex systemsAnonymous *Proceedings of the 3 rd Annual Predictive Methods Conference, Veros Software*, 2003.

TSAI, Y., WANG, K. and TSAI, L., 2004. A study of availability-centered preventive maintenance for multi-component systems. *Reliability Engineering & System Safety*, 6, vol. 84, no. 3, pp. 261-270 ISSN 0951-8320. DOI http://dx.doi.org/10.1016/j.ress.2003.11.011.

TUKKER, A., 2004. Eight types of product?service system: eight ways to sustainability? Experiences from SusProNet. *Business Strategy and the Environment*, vol. 13, no. 4, pp. 246-260 ISSN 1099-0836. DOI 10.1002/bse.414.

TURBAN, E., SHARDA, R., DELEN, D. and EFRAIM, T., 2007. *Decision support and business intelligence systems.* Pearson Education India.

UHLMANN, E., GABRIEL, C., RAUE, N. and STELZER, C., 2011. Influences of the IPS2 Business Model on the Development of a Micro Milling Spindle, pp. 57-62 ISSN 978-3-642-19688-1. DOI 10.1007/978-3-642-19689-8_12.

UHLMANN, E., H. MEIER, H.G. BOCHNIG C, K. SADEK and C. STELZER. Customer driven development of Product -Service-SystemsAnonymous *Innovation Production Machines and Systems Conference*, 2008.

ULRICH, K., 1995. The role of product architecture in the manufacturing firm. *Research Policy*, 5, vol. 24, no. 3, pp. 419-440 ISSN 0048-7333. DOI http://dx.doi.org/10.1016/0048-7333(94)00775-3.

UUSITALO, L., 2007. Advantages and challenges of Bayesian networks in environmental modelling. *Ecological Modelling*, vol. 203, no. 3, pp. 312-318.

Van de Ven, Andrew H, DELBECQ, A.L. and KOENIG JR, R., 1976. Determinants of coordination modes within organizations. *American Sociological Review*, pp. 322-338.

Van der Gaag, Linda C, S. RENOOIJ, C.L. WITTEMAN, B.M. ALEMAN and B.G. TAAL. How to elicit many probabilitiesAnonymous *Proceedings of the Fifteenth conference on Uncertainty in artificial intelligence*, 1999.

VANDERMERWE, S. and RADA, J., 1989. Servitization of business: adding value by adding services. *European Management Journal*, vol. 6, no. 4, pp. 314-324.

VANS, O., 1998. A belief network approach to optimization and parameter estimation: application to resource and environmental management. *Artificial Intelligence*, 5, vol. 101, no. 1–2, pp. 135-163 ISSN 0004-3702. DOI http://dx.doi.org/10.1016/S0004-3702(98)00010-1.

VISNJIC, I. and B. VAN LOOY. Can a Product Manufacturer Become a Successful Service Provider? In Pursuit of a Business Model that Fosters Complementarity between Product and Service Activities PerspectivesAnonymous *Academy of Management Conference*, 2011.

VLADIMIROVA, D., EVANS, S., MARTINEZ, V. and KINGSTON, J., 2011. Elements of Change in the Transformation towards Product Service Systems. In: J. HESSELBACH and C. HERRMANN eds., Springer Berlin Heidelberg,01/01, pp. 21-26 ISBN 978-3-642-19688-1. DOI 10.1007/978-3-642-19689-8_6.

W.H. Ip, C.K. Kwong and FUNG, R., 2000. Design of maintenance system in MRPII. *J of Qual in Maintenance Eng*, 09/01; 2015/05, vol. 6, no. 3, pp. 177-191 ISSN 1355-2511. DOI 10.1108/13552510010341199.

WALKER, W.E., HARREMOÃ«S, P., ROTMANS, J., VAN, d.S., VAN ASSELT, M.B.A., JANSSEN, P. and KRAYER, v.K., 2003. Defining Uncertainty: A Conceptual Basis for Uncertainty Management in Model-Based Decision Support. *Integrated Assessment*, 03/01; 2011/12, vol. 4, no. 1, pp. 5-17 ISSN 1389-5176.

WALLSTEN, T.S., BUDESCU, D.V. and ZWICK, R., 1993. Comparing the Calibration and Coherence of Numerical and Verbal Probability Judgments. *Management Science*, Feb., vol. 39, no. 2, pp. 176-190 ISSN 00251909.

WANG, X. and DURUGBO, C., 2013. Analysing network uncertainty for industrial product-service delivery: A hybrid fuzzy approach. *Expert Systems with Applications*, vol. 40, no. 11, pp. 4621-4636.

WARD, S. and CHAPMAN, C., 2003. Transforming project risk management into project uncertainty management. *International Journal of Project Management*, vol. 21, no. 2, pp. 97-105.

WARRINGTON, L., J.A. JONES and N. DAVIS. Modelling of maintenance, within discrete event simulation Anonymous *Reliability and Maintainability Symposium, 2002. Proceedings. Annual*, 2002.

WECK, O.D., ECKERT, C., WECK, O.D.and ECKERT, C., 2007. *A Classification of uncertainty for early product and system design.*

WETZER, M., DAVID, P.W.I., WEIR, P.E., GARROW, G.R. and NEWTON III, C.P., 2006. *Managing Maintenance for an Item of Equipment*.

WILLETT, A.H., 1901. *The economic theory of risk and insurance.* The Columbia university press.

WINKLER, R.L., 1967. The assessment of prior distributions in Bayesian analysis. *Journal of the American Statistical Association*, vol. 62, no. 319, pp. 776-800.

WISSE, B., S. VAN GOSLIGA, N. VAN ELST and A. BARROS. Relieving the elicitation burden of Bayesian Belief Networks. Anonymous *Sixth Bayesian Modelling Applications Workshop on UAI*, 2008.

WITTEMAN, C. and RENOOIJ, S., 2003. Evaluation of a verbal–numerical probability scale. *International Journal of Approximate Reasoning*, vol. 33, no. 2, pp. 117-131.

YANG, R. and BERGER, J.O., 1996. *A catalog of noninformative priors.* Institute of Statistics and Decision Sciences, Duke University.

ZEITHAML, V.A., PARASURAMAN, A. and BERRY, L.L., 1985. Problems and strategies in services marketing. *The Journal of Marketing*, pp. 33-46.

ZHANG, Y. and WILDEMUTH, B.M., 2009. Qualitative analysis of content. *Applications of Social Research Methods to Questions in Information and Library Science*, pp. 308-319.

ZHANG, Y. and ZHANG, L., 2014. Organizing complex engineering operations throughout the lifecycle. *Journal of Service Management*, 10/14; 2015/06, vol. 25, no. 5, pp. 580-602 ISSN 1757-5818. DOI 10.1108/JOSM-07-2013-0182.

ZIMMERMANN, H.-., 2000. An application-oriented view of modeling uncertainty. *European Journal of Operational Research*, 4/16, vol. 122, no. 2, pp. 190-198 ISSN 0377-2217. DOI http://dx.doi.org/10.1016/S0377-2217(99)00228-3.

ZIO, E. and PEDRONI, N., 2013. *Literature review of methods for representing uncertainty.* FonCSI.

Appendices

The following appendices enlists and describes various methods in BN modelling (Appendix A), questionnaire for validation of BN structure (Appendix B), definition of the variables (Appendix C), characterisations of uncertainties (Appendix D) and questionnaire pack for elicitation of prior and conditional probability distribution (Appendix E) and tables of change in beliefs for sensitivity analysis and scenario analysis (Appendix F).

Appendix A - Bayesian Network Modelling

This appendix presents the various methods that could be employed to derive BN structure and methods to derive conditional probability distribution.

I Structure of Bayesian Networks

After reviewing the literature, it was found that BN structure can be derived in the following different ways.

i) From expert knowledge
ii) From data
iii) Using data and expert knowledge
iv) Using literature and data
v) From literature data

i) Learn from Expert Knowledge

Constructing the structure of BN by hand is a difficult option, especially when the dependent variables are not known by the domain experts (Daly et.al. 2011). In the context of building the structure of large BNs, Neil et.al. (2000) discovered that there were a small number of generally applicable "building blocks" from which all the BNs could be constructed. These building blocks can be combined into objects and which in turn can be combined into larger BNs, using simple combination rules and by exploiting ideas from Object Oriented BNs (OOBNs). The idioms came about from the finding that experts apply very similar reasoning over subtly different prediction problems and faced the same kind of difficulty in trying to represent their ideas in the BN model (Neil et.al. 2000) and they found the following problems for knowledge engineers in deciding which edge direction to choose; whether some of the statements they wished to make were actually uncertain and, if not, whether they could be represented in a BN; what level of granularity was needed when identifying nodes in the BN and whether competing models could somehow be reconciled into one BN model at all. As a result of these experiences and the problems encountered when trying to build reasonable graph models Neil et.al. (2000) identified a small number of natural and reusable patterns in reasoning to help when building BNs. These patterns were termed as idioms and refer to specific fragments of the BN graphical structure that represent very generic types of uncertain reasoning. They synthesised five idioms, which are definitional or synthesis idiom, cause-consequence idiom, measurement idiom, induction idiom and reconciliation idiom. These idioms act as a library of patterns for the BN development process, where knowledge engineers simply compare their current problem, as described by the expert, with the idioms and reuse the appropriate idiom for the job. Xuan et.al. (2007) propose knowledge elicitation tools to build and quantify the BNs exclusively using expert knowledge, where knowledge of multiple experts is combined to enhance the validity of the obtained BN structure.

They argue that domain experts can build and quantify BNs using their knowledge and experience so as to achieve rapid modelling as well as enhanced accuracy and also because BNs represent causal semantics, which are a natural manner of reasoning used by experts. They elicit dependencies between variables from experts through a 'causal relationship questionnaire', where the experts specify whether the causal relationship is direct or indirect and hence, identifying parent nodes and intermediate nodes of the BN structure. The conditional probabilities are determined by adopting probability scale method (Renooij and Witteman, 1999).

ii) Learn From Data

Learning the structure of BN from data refers to a problem of selecting a probabilistic model that explains a given set of data and there is abundance of literature in attempts to understand and provide methods of learning structure from data (Daly et.al. 2011). Hence, learning network structures from data is sometimes referred to as model selection problem, where each network corresponds to a distinct model and one is to be selected based on the data and this entails sample complexity and computational complexity (Buntine, 1996). Learning structure involves selection from an exponential number of network structures and in turn rendering values to possibly an exponential number of real values and this aspect of learning increases the number of cases required for training, which is called as sample complexity as well as the time or space required for optimisation is called as computation complexity. Buntine (1996) further distinguish three phases in learning network structure from data as small sample, medium sample and large sample phases. In small sample, learning corresponds to going with one's biases or priors. Large sample results in learning close to the "true" model with high probability, where "close" is measured according to some reasonable utility criteria such as mean-square error or Kullback-Leibler distance. Medium sample phases depends on the algorithm used, where some algorithms perform better than others, depending on how well their particular biases align with the "true" model.

Daly et.al. (2011) provide an extensive review of literature on methods for learning structure of BNs, learning the parameters of BNs, they also discuss the various algorithms for performing inference in BNs, they also shed some light the methods to test the reliability and stability of the learnt BN and some methods for speeding computation in BN is also reviewed. The review presented by Daly et.al. (2011) attempt to capture and review a variety of methods for learning the structure of BNs, hence this section presents a zest of it and evaluates the approach of learning structure from data, for potential use in this research. Learning the structure has its share of complexity, a simple look at the number of possible Directed Acyclic Graphs (DAGs) for a given number of nodes will indicate the problem is hard, for example for every 10 nodes there are 4.23×10^{18} possible DAGs (Daly et.al. 2011). Three main methods for learning the structure of BNs, are score and search approach through the space of BN structures, a constraint-based approach that uses conditional independencies identified in the data and dynamic programming approach. Most of these approaches are discussed based on the various algorithms created to implement these methods. However, we are only discussing the generic manner in which the methods work and do not dwell into the details of the various algorithms.

iii) Search and score approach through the space of BN structures

Various heuristic algorithms and scoring functions have been discussed under this method. Since searching for BN structure is a hard problem, various heuristic algorithms are generally used to explore the search space, the most basic of which are greedy searches (GSs). Genetic and evolutionary algorithms are also used for this purpose. These algorithms generally comprise of a search space consisting of the various allowable states of the problem, each of which represents a Bayesian network structure; a mechanism to encode each of the states; a mechanism to move from state to state in the search space; and a scoring function to assign a score to a state in the search space, to see how good a match is made with the sample data. Scoring criterions must be defined that allows for good scores when the structure matches the data well. Maximum likelihood estimator is one of the simplest criterion, which returns the complete graph, the one with the most parameters. Most scoring criteria consists of two parts, one that rewards a better match of the data to the structure and one that rewards a simpler structure. Some of the other criterions used are Bayesian Dirichlet (BD) criterion, Bayesian information criterion (BIC), Akaike information criterion (AIC), MDL and minimum message length (MML).

Hence, the strategy for learning BNs in this method employs heuristic search while scoring network structures. Simple algorithms such as greedy search can generate 'good enough' network structures and also work well with smaller data sets, unlike the conditional independence testing which require large datasets to unearth structures. This method has received the most attention in literature and hence is more developed. However, as discussed above, search algorithm, scoring function and search space are the issues faced in its implementation. Global search strategies such as genetic algorithms, simulated annealing etc. can produce better solutions at the cost of longer computation times, while greedy algorithms tend to be cornered in local maxima.

iv) Finding structure using conditional independencies

The other method for learning the structure of BNs is using conditional independencies obtained from statistical tests on the data. Daly et.al. (2011) discuss various algorithms existing to uncover structures from Conditional Independence (CI) statements. The mathematical basis for explaining CIs is presented in beginning of this section. This method is typically used when trying to detect causal relations between variables, however the disadvantages include problems with small sample sizes, missing data and the requirement for a single level of significance to be chosen for the statistical testing of conditional independence. When CI testing is mixed with score and search techniques, a hybrid solution to learning structures is produced.

v) Hybrid search strategies

Under this category, Daly et.al. (2011) discuss hybrid methods that have the pros of score-and-search methods and conditional independence methods. Score-and-search typically works better with less data than CI testing and with probability distributions that admit dense graphs. They also allow probability distributions over models to be easily represented and have better mechanisms for dealing with missing data. On the other hand, CI testing methods works well with sparse graphs. They are generally quick and have good ways of finding hidden common causes and selection bias. Various hybrid algorithms implementing the hybrid method have also been discussed.

vi) Dynamic programming

This method is similar to the score-and-search approach, but does not have the search aspect and can perform feasible exact learning for moderate numbers of variables (up to about 30). It uses dynamic programming to compute optimal models for a small set of variables and in some cases combine these models.

In addition to the above methods of building structure of BNs, model averaging, parallel learning, online learning, active learning and local feature learning were also mentioned by Daly et.al. (2011). When there is not much data and no one model rises high above the rest, the learning procedure can return multiple model, model averaging is used. In order to speed up learning of BN structure, multiple computing resources can be used and evaluating different neighbouring states in parallel. For example in score and search method, the scoring functions can be evaluated in parallel and hence reducing the bottleneck of finding sufficient statistics. Usually learning a BN involves a block of data given to an algorithm which learns the structure and parameters for that structure. When data are continuously being supplied to a system, online learning takes place. Active learning involves use of observation data, where the learner able to intrude and ask for data, where particular variables have been manipulated to certain values. When large BN graphical structures with large number of variables have small parts with small number of variables, local features are learned directly from data. This is referred to as local feature learning.

vii) Using data and expert knowledge

Expert knowledge about a given domain can be codified into BNs, by experts defining structural restrictions such as existence or absence of arcs and/or edges and causal ordering of parent variables (Cano et.al. 2011). In circumstances of low amount of data, admitting specific knowledge from expert for learning the structure of BN is a fundamental task (Daly et.al. 2011) and is an excellent solution to reducing the inherent uncertainty of the models retrieved by automatic learning methods (Cano et.al. 2011). The typical approach supplementing automatic learning methods of BNs from data, is the elicitation of informative prior probability distributions of the graph structures (Heckerman et.al. 1995, Cano et.al. 2011).

In their paper, Buntine (1996) suggest that medium sized samples pose a twist on the problem of knowledge acquisition, where frequently data should be complemented with prior knowledge and constraints, if reliable and useful results are to be obtained. And this Prior knowledge can often only be obtained from domain experts by the manual process of knowledge elicitation. Daly et.al. (2011) discuss difficulties associated to knowledge elicitation and types of knowledge that would aid defining the BN structure. There is difficulty in bringing data and expert knowledge together, as they are often in different forms. The types of knowledge an expert can provide can be related to ordering of variables (total or partial), a prior network, prior equivalent sample size etc. The type of knowledge to be elicited from expert depends on the algorithm implemented, for examples, score and search method requires elicitation of prior distribution from the expert.

Cano et.al. (2011) propose a methodology for integrating expert knowledge to automatic learning using data. The implement Mont Carlo simulations, which does not rely on the expensive elicitation of prior distributions but only demands expert information about those direct probabilistic relationships between variables which cannot be reliably learned from data. Buntine (1991) also focussed on the problem of introducing expert knowledge about structure of the network. Their methodology was first initiated by total ordering of the variables by the expert. In the second step, the experts specified their belief on the strength of each potential parent is a real parent. Shades of grey was used to pictorially present these strengths, where black arcs indicated definite parents (with a prior probability of one), missing arc indicated non-definite parents (a prior probability of zero) and grey arcs indicated the partial beliefs of experts (prior probability ranging from zero to one). After the experts expressed their beliefs, automatic updating of BNs was done to introduce information of the data and posterior probability of each edge was displayed given the prior knowledge from the experts. This allowed the data to modify previous shades of grey for each edge, whilst the data supplementing expert knowledge.

Heckerman et.al. (1995) propose an interactive methodology to integrate expert knowledge to automatic learning of BN from data. The methodology demands the expert to provide his/her knowledge during the learning process for example, presence/absence of some edges of the graphs, leading to an interaction between the system and user. It employs Monte Carlo techniques and Importance Sampling (IS) techniques to approximate posterior probability given the learning data and once approximation of this probability distribution is available, model uncertainty can be measured via the entropy function of this distribution with the aim of reducing as far as possible the entropy of the probability distribution and hence obtaining BNs that are more accurate with reduced uncertainty.

viii) Using literature and data

In complex statistical models like BN, where data is scarce or high levels of noise are present, electronic literature could be used to for prior knowledge as they available in abundance and at the same time the explicit semantics and computational power of BNs, create an opportunity for the integration of domain literature with statistical data (Antal et.al.2002). Antal et.al. (2002) also proposed an extended representation of BNs called Annotated BN, which enabled them to stablish a connection between computation model (which is BN) with textual domain knowledge and this representation defines an hierarchy of classes over the domain variables and attached of free text to the objects of representation, such as values, variables, edges, dependency models and classes. In their paper, they describe a language for information retrieval with Annotated BNs which supports the manual construction of BNs, evaluate and present results on scoring BN sub-structures by deriving text-based prior distribution over the space of BN structures and also update this to a posterior with statistical data using a case from ovarian cancer domain.

ix) From literature or text

There is demand for techniques and tools which can automatically construct Bayesian networks from massive text or literature data, due to ease of availability of massive text or literature data (Antal et.al.2006, Raghuram et.al. 2011). BNs is a tool, which can effectively integrate knowledge obtained from literature with statistical data (Antal et.al. 2006).

Raghuram et.al. (2011) use literature mining as a significant source of data to build and update BNs by extracting information related to causal associations, statistics information and experimental results from research articles, journals etc. by implementing a data driven tool called AutoBayesian. It was developed using Microsoft SQL Server 2009 Express edition and a BN tool called Netica and has been tested in geriatrics health care. The methodology implemented by Raghuram et.al. (2011) involved two key steps, firstly deriving confidence measure for causal associations mined from research articles. The weighted average of influence measure and evidence level gives confidence measure, where former measure is in relation with the source journal and latter is related to level of causal evidence mined. Secondly, the methodology integrates causal mapping with BN by mapping noun phases to nodes in a BN, handling cycles or loops identified whilst integrating with the existing BN structure and finally creation of new links between nodes in the network, if does not form a loop. The results and suggestions are generated and displayed on the screen, where the expert can choose to automatically accept the suggestions or review them by selecting the interesting suggestion.

Antal et.al. (2006) also proposed generation of BN models from scientific publication to hold up the idea of construction of real-world models from free text literature. They discover and extract latent causal dependency relations from the domain literature using minimum linguistic support by employing BN based text mining. They focus on extracting definitive causal relations between entities rather than tentative status or relations, discover new relations and snipping redundancies by providing a domain-wide model. They state conceptual phase, associative phase, causal relevance phase and causal effect phase as sequential phases of uncertainty in relation to biomedical domain. The conceptual phase has uncertainty over the ontology, associative phase has uncertainty over the relation between entities reported in literature as indirect, associative hypotheses or frequently as clusters of entities, causal relevance phase has uncertainty over causal relations and causal effect phase has uncertainty over the strength of the autonomous clusters comprising of causal relations.

II Elicitation of Conditional Probability Distribution

i) Direct Elicitation of Conditional Probability

In this method, individual probabilities for different combination of states of the parent nodes need to be elicited. The number of probabilities grows exponential to the number of parent nodes (Clemen et.al. 2000; Das, 2004; Baker and Mendes, 2010) and this method of eliciting has another challenge, maintaining the consistency of the probabilities elicited, which is the ability of the experts to coherently provide probabilities at the level of detail required, which is limited by the cognitive processing of human short term memory capacity (Wisse et.al. 2008). It is also perceived as difficult for an expert to think about probabilistic relationships in terms of conditional distributions, however if the expert can state individual probabilities, it results in a more complete understanding of those relationships and possibly a more rigorous assessment (Ravinder et al. 1988).

ii) EBBN Method

EBBN (Elicitation for Bayesian Belief Networks) method has been discussed in literature (Hansson and Sjökvist, 2013; Wisse et.al. 2008) and a summary of it is presented below. It uses piecewise linear interpolation based on the ranks of the states of parent node's and child node, which is ordered on the form low to high. The number of assessments required from the expert is as many rows of the CPT as there are child states and one weight for each parent node. It also does not take into account the interdependent effects that may exist between the parent nodes.

The CPT in this method is obtained by ordering the states of the child node along with the ordering of the parent nodes with respect to the influence they exercise (Wisse et.al, 2008). The number of probabilities the expert is required to assess is linear to the number of conditioning parent nodes. If the expert is confident of a certain conditional probability, the calculated probability using EBBN method can be replaced with the expert's belief. Wisse et.al. (2008) did a comparison of EBBN method of dependency elicitation with normal copula vine approach (Hanea and Kurowicka, 2008) and simple uniform distribution. They found that the performance of EBBN method was comparable to the copula vine method, however it was deemed distinctly better than that of uniform distributions.

However, this method has a shortcoming in terms of its inability to produce large difference between two adjacent probabilities of a state in the CPT. The method also includes inaccuracies due to approximation of the probabilities which are elicited from the expert and it is suggested that due to this feature of the method, it is apt for using it as a first step in an iterative procedure for stepwise refinement of probability assessments. Secondly, there is a chance that the number of assessments required from the expert could increase beyond the number of probabilities in the CPT and it happened when the number of states of the child node which needs CPT is greater than number of assignments for the conditioning variables.

iii) Likelihood Method

This method and the ones discussed below require few assessments from the experts and hence are time efficient methods. In likelihood method, the assumptions which hold are that the states of the child node is assumed to be a typical distribution. Secondly, the log likelihood of the parents are assumed to be independent rather than the Conditional Probability (CP) itself, unlike influence weights method (Kemp-Benedict, 2008). The log likelihood can be represented as a sum of independent terms, one for each of the parent nodes and it links the parent nodes and the child node, by regulating the extreme variations in the states of the parents and child node.

This method requires the following assessments from experts (Hansson and Sjökvist, 2013),

1) A typical distribution represents the normal state of affairs and its specific form is not of importance.
2) the base
3) a weighting factor for each state of the child node
4) a weighting factor for each state of the parent nodes

The advantage of this method is that it requires only one value for each state of each parent node, the experts are asked to assess influence weights rather than probabilities (Kemp-Benedict, 2008) and it works for a node with a single parent as well (Hansson and Sjökvist, 2013). The disadvantage of this method is that it cannot be directly integrated to the Bayesian network, although the algorithm that generates the CPT is easy to implement and it gets very complex when the node has more than three states.

iv) Weighted Sum Method

Weighted sum algorithm has been discussed in literature (Hansson and Sjökvist, 2013; Das, 2004) and a summary of it is presented below. The number of assessments required from the expert is linear rather than exponential and it is equivalent to as many rows of the CPT as there are states in the parent nodes. A shortcoming of this method is that it is based on the concept of compatible parental configuration, which can be hard for an expert to assess.

There is minimal assessments required from the expert which is fed as input to the algorithm, which then populates the CPT by computing appropriate weighted sums of the elicited distributions. The expert needs to assess a set of weights that quantify the relative strengths of the influence of the parent nodes on the child node and a set of probability distributions, corresponding to the compatible parental configurations for every parental state. And hence the number of assessments grows linearly with the number of parent nodes. This method too neglects the co-active influence between the parent nodes on the child node and only considers the parents individual influence on the child node. Das (2004) have implemented the methods of information geometry, to demonstrate that the logic behind the algorithm emulates the judgemental strategy used by experts. A validation of the method was also carried out by

Baker and Mendes (2010), who presented two empirical studies to assess the weighted sum algorithm efficiency and prediction accuracy and found the algorithm to be highly accurate whilst making prominent reductions in elicitation.

v) Rank Correlation Method

The assessment of prior probability distribution and dependency between the variables are naturally carried out separately and this is evident when using copulas to model the dependency structure between the variables (Clemen and Reilly, 1999). They further elaborate that a joint distribution is culmination of the marginal distributions for the individual variables and a copula that links the variables. There are different families of copulas such as normal, franks copula etc., which can be used to define relations among variables by specifying rank correlations. However, when sampling a large BN structure with a copula, computation in terms of evaluations of multiple integrals is very time consuming, but this disadvantage fades when using normal copula (Hanea and Kurowicka, 2008).

Several researchers have used (conditional) rank correlations to specify the dependency between variables. Cooke et.al. (2007) presented a continuous non parametric Bayesian network to model air transport safety, where both field data and expert assessment were applied to specify prior probabilities and (conditional) rank correlations for the probabilistic nodes. It also encapsulates functional nodes that represent fault tree modelling. Kurowicka and Cooke (2005) endorse the use of rank correlations to capture dependency between variables for several reasons, such as the numerical values of rank correlations are algebraically independent of all the factors including the conditional independence implied by the graph, univariate marginal distribution along with the copula representing the dependency structure between the nodes uniquely specify the joint distribution and any additional dependencies can be accommodated without altering the values already chosen, conditioning can be achieved using simulation except for joint normal copula, where it can be realised analytically and protocols for eliciting rank correlations from experts is available and they are independent of the nodes marginal distribution. Druzdzel and Van der Gaag (1995) use the same concept as rank correlation for interpretation of the qualitative influences between variables expressed by domain experts for quantifying an HIV infection related Bayesian network. They describe qualitative influence to be a symmetric property between two variables X and Y, with sign of probabilistic interaction as positive sign from X to Y, indicates an increase in variable X results an increase in variable Y and negative, when an increase in variable X results a decrease in variable Y. Four approaches for the assessment of rank correlations, are described below.

a) Direct Elicitation of Rank Correlation

Clemen et.al. 2000 proposed elicitation of rank correlations directly from experts. They conducted two experimental studies to be able to prescribe an appropriate method for the elicitation of dependency between variables. In their experiment, they compared accuracy of six different methods for assessing dependence, which included, S (strength of relationship), R (correlation), CF (conditional fractile), CNC (concordance probability), JP (joint probability), and CP (conditional probability). They found that simply asking experts rank correlation between two variables consistently performed better than any of the other assessment methods in terms of average absolute error. They endorse direct elicitation of rank correlation as an ideal method for representing dependency between variables because, it has a sound probabilistic foundation for modelling, it is in line with the latest knowledge in behavioural decision theory as well as the current practice in probability elicitation, it is a generic approach that can be implemented in a wide variety of situations, it has a clear intuitive interpretation, experts regard it is as easy and credible and finally it has the implicit ability to be linked to the whole modelling procedure.

b) Statistical approaches

This approach is suitable if the expert has sufficient knowledge of statistical concepts related to rank correlation. An expert may be presented with many scatterplots showing different degrees of correlation and he needs to choose the scatterplot that most closely represents the relationship between the variables for which the assessment is carried out (Morales et.al. 2008). In cases, where the expert lacks sufficient statistical knowledge, training could be provided to familiarise them with the relevant concepts.

c) Probability of Concordance

In this approach, probability of concordance is assessed by the expert and this is used to compute the Kendal’s tau. It is appropriate to use this approach, when the events are expressed in terms of frequency, as the assessment question would not be complex and hence the expert can comprehend the scenario easily to provide an estimate of concordance probability, however it is not apt for situations where assessment is required for one-off events (Clemen and Reilly, 1999).

d) Conditional Fractile Estimates

In this approach, expert is required to provide several conditional estimates and a least squares approach is applied on this assessment to estimate spearman's rank correlation (Clemen and Reilly, 1999). Elicitation of conditional fractiles given a specific condition is cognitively taxing for the expert and is not very common (Clemen et.al. 2000).

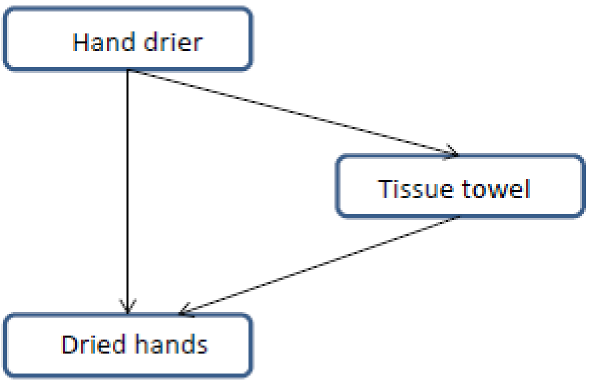
Appendix B - Validation of Bayesian Network Structure

The aim of this activity is to validate a Bayesian Network (BN) structure, which represents a network of related activities using a graphical model. We would like to get your feedback at this stage, before proceeding to capture the information required in the model.

Background on BN

A Bayesian network is a model. A BN structure has nodes representing random uncertainties and directed arcs representing causal or influential relationship between the uncertainties. It reflects the states of some part of a world (uncertainties) that is being modelled and it describes how those states are related by probabilities.

The hand drier example has been discussed earlier. A simple BN is shown below to illustrate these concepts using the hand drier example. The hand drier can have two states functional and non-functional, placing of tissue towels can be yes or no and the dried hands can be yes or no. If the hand drier is functional, then we can have our hands dried. And in the opposite case, if the hand drier is not functioning, then tissues are used. This can also cause dried hands.



When actual probabilities are entered into this net, it can be made to answer a number of useful questions, like, "if the hand is dried, what are the chances it was caused by the hand drier or the tissue towels", and "if the chance of the hand drier breaking down is more, what is the trade-off between cost of tissue towels or the cost of buying a new hand drier or cost of repairing the existing hand drier".

In the subsequent pages, a BN for factors affecting *Turnaround time* and factors affecting *Operational Readiness* is presented. Followed by a likert scale scoring table. Please provide a scoring of your agreement of the causal/influential relations between uncertainties as follows:

Level of Agreement

1 – Strongly disagree
2 – Disagree
3 – Neither agree or disagree
4 – Agree
5 – Strongly agree

Please provide your score on the level of agreement. For example, in your opinion, if the service demand has a strong influence on the availability of spares then you should write 5. Any suggestions the unit of measurement for the various uncertainties will be welcome. For example you could mention the unit of measurement for *Service demand* as repair tasks per month/year or linguistic descriptors such as High/Medium/Low.

1--------------------------2-------------------------3-----------------------4------------------------5

Strongly **Disagree** **Neither agree** **Agree** **Strongly disagree**
or disagree

Likert Scoring Table

Influencing factor/ Cause	**Influencing factor/ Cause**	**Scoring**	**Unit of measurement**
Service Demand	Availability of spares (OEM facility)		
No Fault Found	Availability of spares		
Requisition Wait Time	Availability of spares		
Safety Stock	Availability of spares		
Production Lead Time	Safety Stock		
Service Demand	Availability of personnel		
Availability of spares	Turnaround time		

Equipment usage	Failure rate		
Remaining useful life	Failure rate		
Availability of spares	Equipment readiness		
Availability of personnel	Turnaround time		
Availability of test equipment	Availability of work bench		
Availability of work bench	Turnaround time		
Customer damage	Failure rate		
Degree of contracting	Supply chain visibility		
Failure rate	Service demand		
Infrastructural capability	Service demand		
Level of confidentiality	Supply chain visibility		
Level of skill & knowledge	Availability of personnel		
Level of skill & knowledge	Service personnel efficiency		
Service personnel efficiency	Turnaround time		
Operating environment	Failure rate		
Quality of support	Supply chain visibility		

Intellectual property	Service demand		
Retrograde duration	Service demand		
Service demand	Availability of work bench		
Supply chain visibility	Requisition wait time		
Task complexity	Availability of personnel		
Task complexity	Service personnel efficiency		
Transport time	Availability of spares		
Turnaround time	Availability of spares		
Demand for contractor/in-house spares	Availability of spares		

Please also provide any additional comment or feedback:

- Does the model structure (the number of uncertainties, uncertainty labels and arcs between them) look the same as you and/or literature predict?
- Is each uncertainty of the network discretised/separated into sets that reflect your knowledge? For eg. all uncertainties with discrete values such as *Supply chain visibility* has high, medium & low values; *Service personnel efficiency* has high, low & medium values. Do these descriptors suffice, if not please provide alternatives.

Appendix C - Explanation of Variables in PSS

❖ **Administrative and customs' cost** – It refers to cost incurred due to regulations with regard to customs and cross-border transportation which can interfere with the transport of spare parts and service personnel onto customer site.

❖ **Attitude and behaviour of service personnel** – It refers to the behaviour and appearance according to a required standard in order to not have a negative impact on customer satisfaction and its more significant in cases where the service personnel is the only point of interaction with the customer.

❖ **Availability of Back office/ Administrative personnel** – It refers to the timely handling of service request by availability of administrative personnel in order to avoid logistics delay time and sustain operational availability.

❖ **Availability of IT systems** – It refers to IT systems required to access data and documentation. For example: Work cards are replaced by IT systems generating service task orders, accessible to remotely placed service personnel.

❖ **Availability of personnel (Production/ Service) -** It refers to the number of production personnel engaged in the production of a single equipment

❖ **Availability of spares –** It refers to the probability of a serviceable spare available at a point in time.

❖ **Availability of test equipment -** It refers to the probability of a functional test equipment available at a point in time.

❖ **Availability of work bench -** It refers to the probability of that a work bench suitable to perform service task by service personnel is available at a point in time.

❖ **Batch size–** It refers to the number of products or spares that will be produced after a machine has been setup and aids in inventory analysis.

❖ **Changeover time (for production) –** It refers to the machine changeovers and setups required to switch processing to a different operation or a different lot of products.

❖ **Contract escalation clauses -** It is a clause in a contract that guarantees a change in the agreement price once a particular factor beyond control of either party affecting the value has been determined. For example, contract that adjusts for inflation.

❖ **Cost of raw materials -** It is the cost of direct materials which can be easily identified with the unit of production. This cost poses a major risk to the OEM as it could change significantly after the pricing of the PSS has been agreed

❖ **Cost efficiency -** It is producing optimum results for the expenditure. For example, within the customer organisation, there are multiple internal customers. Where, the budget-holders demand for cost efficiencies should not be allowed to over-ride the military commanders' rightful expectation of demand-flexibility. They need to sit side by side.

❖ **Cost of tool kit/ Consumables -** It is the cost of supplies, eg. Lubricants, filters, which need to be replenished at regular intervals.

❖ **Cost of access to facility (Rent/ Lease) -** It refers to the rental or lease costs of the factory or facility required to deliver PSS.

❖ **Cost of diagnostic technology -** It is the cost of additional diagnostics equipment integrated into the product so as to enhance the overall system performance.

❖ **Customer budget/ customer affordability -** It is the degree to which the Through Life Cycle Cost of an individual project or program is in consonance with the long range investment capability and evolving customer requirement.

❖ **Customer damage –** It refers to damage induced by customer and are usually can be detected by visual inspection of the hardware. For example: broken PCB board, broken key panel of MHDD.

❖ **Customer participation -** Customer participation is defined as the extent to which customers provide resources in the form of time and/or effort and/or information provision during the service production and delivery process.

❖ **Customer satisfaction/ Customer loyalty -** It refers to measurement of the effectiveness of service or value in use which translates to customer satisfaction, feedback and loyalty, which is rather subjective in most cases.

❖ **Level of customer retention -** It is the activity that a selling organization undertakes in order to reduce customer defections.

❖ **Customer wait time (CWT) -** It is the total elapsed time between issuance of a customer order and satisfaction of that order.

❖ **Dates for design refresh -** It refers to the change the design of products and/or systems consistent with shifts in demand and with changes in the availability of the materials and components from which they are manufactured. Prediction of accurate refresh dates at the component level insulates against the impact of obsolescence.

❖ **Degree of subcontracting -** It refers to the number of contractual arrangements with stakeholders in the supply network assigned with different outsourcing responsibilities. For e.g. the Tornado aircraft had some 350 separate contracts for the MoD team to manage.

❖ **Degree of value co-creation –** It refers to the degree to which an organisation engages its customers in the creation of value through shared innovation, design, and other discretionary behaviours**.**

❖ **Demand for spares –** It refers to the spares demanded for each service task and could be categorised as demand for in-house spares or contractor supplied spares.

❖ **Diagnosis time -** It is the time required to localise the cause of equipment failure. Some failures have a significant diagnosis time.

❖ **Discount rate -** It is the interest rate charged to commercial banks and other depository institutions for loans received from the Federal Reserve Bank's discount window.

❖ **Effectiveness of diagnostics technology -** It is the measure of the degree of effectiveness of the diagnostic mechanism

❖ **Effectiveness of communication tools -** It is the degree to which communication tools chosen by the organisation such as IT systems, documentation etc. achieve the desired level of communication.

❖ **Efficiency of energy -** It refers to the amount of energy required to provide products and /or services.

❖ **Employee motivation -** It is the level of energy, commitment, and creativity in the personnel in order to achieve the goals of the organisation.

❖ **Employee state(Physical health-illness, Fatigue Impact of personal events –family issues) -** It is the level of physical health, fatigue caused due to unregulated hours and frequent night work characteristic of maintenance and personal events, which impacts the personnel efficiency whilst performing service task.

❖ **Equipment efficiency -** It is the actual output/ideal output given a reference level of nominal parts processed with the given piece of equipment.

❖ **Exchange rate -** It is the price of a country's currency in terms of another currency.

❖ **Failure of software (including operating systems) -** It is the failure of the software installed on the equipment.

❖ **Failure rate -** It is the frequency with which an engineered system or component fails, expressed, for example, in failures per hour.

❖ **Fitting of modification kits in the field cost -** It is the cost incurred during equipment upgrades, which include for example in the case of avionics, power, cooling, wiring harnesses, mounting fixtures, cables, connectors, etc.

❖ **Human errors -** Errors can be described as active failures that lead directly to the incident, and latent failures whose presence provokes the active failure.

❖ **Inflation rate** – It is the sustained increase in the general price level of products and services in an economy over a period of time.

❖ **Infrastructural capability -** It refers to the infrastructure required to make PSS offering more profitable and sustainable. Number of service center's, specialist equipment etc. needed to meet demand.

❖ **Infrastructural complexity/ Facility design -** It refers to the level of involvement of substantial bespoke or highly customised hardware and software elements incorporated into the infrastructure. It is involves transition investments in infrastructure from organisations that are product oriented to design, build, install, etc., affording a convenience to provide service.

❖ **Interest rate -** An *interest rate* is the rate at which interest is paid by a borrower (debtor) for the use of money that they borrow from a lender (creditor).

❖ **Labour cost / Labour fee -** It is defined as the total expenditure borne by employers in order to employ workers. For example, the industrial maintenance market traditionally offers “hours” of electrical or mechanical engineers for a fixed fee per hour. They often find themselves competing against other service suppliers on the hourly rate charged.

❖ **Labour hours -** It refers to the number of hours a service personnel works in a week.

❖ **Level of resource sharing -** It is the sharing of resources such as service personnel and/or equipment. This occurs due to the high level of collaboration associated with PSS, where even customers’ resources can be used by the OEM.

❖ **Level of Image/brand identity -** It refers to brand's name, communication style, logo and other visual elements created by the organisation, which is perceived by the customers.

❖ **Level of technical skills/ Skill of the worker -** It is knowing the procedures, rules and likely outcomes of different maintenance actions when involved in a service task. In PSS, manufacturers have opportunities to use their technical knowledge to find ways to deliver same or better value in use while using less energy or material, whilst offers the potential to reduce cost (as well as environmental impact).

❖ **Level of cannibalisation –** It refers to removal of serviceable parts from (for example, from damaged aeroplanes) for use in the repair of other equipment of the same kind.

❖ **Level of Confidentiality (exercised through policies/contracts) -** It refers to an agreement entered into by two or more parties in which some or all of the parties agree that certain types of information pass from one party to the other or that are created by one of the parties will remain confidential. It can also be restrictions extended to access to certain facility, equipment etc.

❖ **Level of cooperation** – It refers level to which the organisation is required to cooperate with customer based on depth of contract, whether it is strategic level , where organisation has proactive stance, who is committed to objectives or tactical level, where organisation takes care of maintenance and cooperates or operational, where organisation is called upon when necessary.

❖ **Level of fit (product and service)** – It refers to the strategic fit between the service intend to be offered and the life cycle stages (Introduction, Growth, Mature and Decline) of the product is fundamental.

❖ **Level of knowledge maturity –** It refers to the scale of knowledge maturity including all tacit and explicit knowledge in the development of PSS ranging from excellent to inferior.

❖ **Level of management support/ effort -** It refers to effort exerted by the management towards planning and supervising functions of maintenance management.

❖ **Level of technical knowledge -** It is the ability to translate technical (or technological) knowledge into practical action. It is vital in PSS maintenance process, a task can be rapidly executed by an expert or more slowly by a lower skilled worker.

❖ **Level of trust -** It refers to reliance on the integrity, strength, ability, surety between stakeholders, which facilitates information exchange and characterises the nature of relationship between them.

❖ **Manpower (Service personnel) efficiency** - It is the ratio of the number of service tasks* performed to the number of labour/working hours.

❖ **Marketing performance -** It is the analysis and improvement of the efficiency and effectiveness of marketing.

❖ **Mean time between failure (MTBF) -** It is usually used only for components that can be repaired and returned to service and is calculated as the total time measured divided by the total number of failures observed.

❖ **Mean time to failure (MTTF) -** It refers to the average time until a component fails, can't be repaired and must therefore be replaced, or until the operation of a product, process or design is disrupted.

❖ **Negotiation cost -** It is the estimated cost negotiated in a cost-plus fixed-fee contract or the negotiated contract target cost in either a fixed-price-¬incentive contract or a cost-plus-incentive-fee contract.

❖ **No Fault Found –** It refers to a reported fault for which root cause cannot be established and results in removals of equipment from service for reasons that cannot be verified by the maintenance process.

❖ **Non-financial incentive** – It refers to incentives of no direct monetary value, for example: reputation by association and the chances of future work.

❖ **Number of components/ sub-systems** - It is the number of components or subsystems in the equipment.

❖ **No. of field facilities/ No. of service centres** - It refers to the number of service facilities as usually products made at a single manufacturing location will be serviced at many service locations around the world due to the distributed nature of the service business. The volumes associated with original manufacture will always be higher than those at the service facility.

❖ **Number of production personnel** - It is the number of personnel required to meet the incoming product demand. It is vital to ensure the scheduled production volume is achieved by the presence required number of personnel.

❖ **Number of service personnel** - It is the number of personnel required to meet the incoming service demand. It is vital to determine the number of personnel required to ensure that the service personnel are utilised to their capacity and a pre-set level of availability and reliability of the equipment is achieved.

❖ **Occurrence of process obsolescence** - PSS are subject to systemic obsolescence, where an old way of performing a process needs to be replaced with new process procedures and protocols.

❖ **Occurrence of skills obsolescence** - It is the state when the skill set possessed by the service personnel is no longer useful and is replaced by new skill requirements for the service task. It occurs due to the systemic nature of obsolescence in PSS

❖ **Occurrence of software obsolescence** - It is the state when the software installed is no longer useful and needs an upgrade.

❖ **Occurrences of component/sub-system obsolescence** - It is the state when the component or subsystem is no longer useful and needs to be replaced due to changes in design etc. with a new component /subsystem.

❖ **Operating experience** - It is the experience gained by repeated performance, which also results in continuous optimisation of service processes by allowing an overall faster and cheaper service execution. Also depending on the number of installed PSS, the OEMs knowledge increases over the use phase

- **Operating parameters/environmental variability/ customer variability (operating environment) –** It refers to condition in which the equipment is used, where there is variation in temperature, humidity, exposed vibration etc., which alters the equipment point of failure.

- **Overflow/ backorder -** It is the fraction of the service calls or demand the system is not able to handle. It is the excess service demand rate that exceeds the organisations capacity to supply it and which are not met immediately.

- **Performance complexity -** A function of the level of knowledge embedded in the performance and/or the level of customer interaction.

- **Performance metric (Turnaround time/ Equipment readiness) -** PSS which are delivered contractually, can have time allocations for different processes, for eg. 30 days turnaround time and the organisation is assessed for the chosen metric and paid accordingly.

- **Point of failure –** It refers to the threshold level of accumulated wear or damage, which designates a non-functioning state or an incipient failure. For example: electronic components function reliably if their resistance, capacitance and voltage stay within design limits, and failure can be said to occur when one or more of these parameters degrades beyond a specified limit.

- **Political climate** – It refers to the impact of nation’s political climate, which affects defence industry’s operations. For example: perceived threats from other nations, could affect the government’s willingness to invest in defence projects.

- **Pricing structure/ Incentive design** - It refers to mechanism for linking the coordination of resources required in availability contracting to the business model. It should take into account true end-to-end costs.

- **Product architecture/ Type of product design -** A modular architecture has one-to-one mapping from functional elements in the function structure to the physical components of the product, and specifies decoupled interfaces between components. An integral architecture includes a complex (non one-to-one) mapping from functional elements to physical components and/ or coupled interfaces between components.

❖ **Product demand -** It refers to how much (quantity) of a product is desired by the customers at various prices and his willingness and ability to pay a price for a specific quantity.

❖ **Product dimensions –** It refers to the physical characteristics of the product such as width, height, weight etc., which could impact the shipping method used, size of inventory etc.

❖ **Production lead time -** Total time required to manufacture an item, including order preparation time, queue time, setup time, run time, move time, inspection time, and put-away time. For make-to-order products, it is the time taken from release of an order to production and shipment.

❖ **Prototype cost -** It is cost of prototypes that can look and function like finished production units. The testing of these prototypes enable to understand the implications of new technology that could influence hardware/software obsolescence.

❖ **Public policies and Legislation Changes** – It refers to changes in UK, EU and international law, regulations, and protocols concerning environmental, safety and social issues. These impacts both the Through-life cost at the outset of the project and the affordability of extant projects.

❖ **Qualification of the machine operator** – It refers to take up of work orders matching their qualification type and their hierarchical position in the organisation with high division of labour and organisations with flexibility allow personnel with electrical and electronic qualifications to take mechanical work orders.

❖ **Quality of support** – Support received from other maintenance and engineering organisations within the supply chain depends, for example: on the competitiveness prevailing among the different stakeholders.

❖ **Quantity of the life-time buy -** It refers to quantity of spares bought in at a single time. Especially for components which are single sourced and its continuous supply is at risk due to commercial factors example: Supplier bought out etc.

❖ **Queuing time -** It is the time between the arrival of equipment at a workstation/service centre and the start of work on it

❖ **Re-certification against regulatory requirements cost -** It is the cost incurred to obtain approval from relevant regulatory agencies for its usage, especially for equipment used in aerospace and defence industry.

❖ **Re-design cost -** It includes the cost of engineering, programme management, integration, qualification and testing. Redesign can be further broken down into categories, e.g. minor (board layout) and major (board replacement)

❖ **Relationship cost -** OEM's have to invest in relationships to be able to provide a PSS. Such transition costs can be of intangible nature and one-off. For example, there is monetary loss, when the stakeholder's partnership has problems and results in breaking up the relationship with a preferred supplier.

❖ **Relative importance of stakeholders/ Node criticality -** It refers to a characteristic of supply chain design, which describes the relative importance of stakeholders. As the stakeholder's criticality increases, they have more influence on any disruptions caused.

❖ **Remaining useful life** – It refers to the useful life left on an asset at a particular time of operation.

❖ **Re-manufacturing cost -** It includes the cost of dismantling, disassembling, cleaning, examine, diagnose, measure, machining of parts, reassembling and testing. It is prescribed that it should not exceed 50% of the value of new replacement.

❖ **Renegotiation cost -** It refers to the cost incurred to discuss again the details of a formal agreement especially in order to change them.

❖ **Renewal period -** It refers to the action of extending the *period* of *validity* of a *contract. In availability contracts*, usually an evergreen period is *renewed* after a short *period*, which is agreed upon by the parties at the outset of the *contract. For example, 5 years*

❖ **Repair/replacement time -** It represents the time required to repair a failed component or replacement of the failed component by an operational component. Modular designs facilitate easy replacement.

❖ **Requisition wait time (RWT) / Order and Ship Time (OST) -** It is the time required to replenish parts both from internal inventories or external source and it is used to measure performance of the entire logistics chain as to how they serve the internal customer (inventory) within the OEM.

❖ **Resource workload -** The activity of all resources is calculated by the ratio of cumulative process time for all resources and the total possible resource working time.

❖ **Response time/ Reaction time/ Responsiveness (service personnel) -** It is the speed in getting back to customer. It depends on factors such as the willingness or readiness of employee to provide service.

❖ **Retention of intellectual property/ Knowledge leak -** It refers to the OEMs loss of control over the product due to outsourcing of maintenance, repair etc. and hence allowing suppliers to gain new capabilities. It may also result in the risk of being locked in by a specific supplier to supply components due to them not revealing the details on design, production etc.

❖ **Retrograde time -** It refers to the delay time in the reverse logistics for failed equipment returned by the customer. This is especially vital in defense sector, where OEM is required to meet performance metrics.

❖ **Safety cases analysis cost -** It refers to the cost incurred to derive assurance of both software and hardware elements of the equipment. It involves global analysis of the system.

❖ **Safety stock -** It is the level of extra stocks also known as buffer stock held to reduce the uncertainty of stock out.

❖ **Service completion rate/System throughput/ Number of service assignments completed per service technician** – It refers to the quantitative measure of the number of service tasks completed by service organisation measured over a finite period.

❖ **Service coverage -** Service coverage represents the scale of servicing relative to a given size of the installed base of products.

❖ **Service demand/ Number of maintenance work orders/ Number of service assignments/ Number of service tasks -** It refers to the number of service tasks that need to be performed to maintain the required level of availability as defined in the contract.

❖ **Service location -** Products made at a single manufacturing location will be serviced at many service locations around the world due to the distributed nature of the service business. The volumes associated with original manufacture will always be higher than those at the service facility

❖ **Service operating efficiency -** Service system's potential operating efficiency is a function of the degree to which the customer is in direct contact with service facility relative to total service creation time for that customer.

❖ **Service preparation time –** It refers to the time spent in ensuring availability of correct maintenance resources, the required documents and spare parts, and the subject of maintenance operations i.e. the equipment will all be available to the service personnel in order to carry out the service task.

❖ **Service recovery** - *It* refers to the actions a service provider takes in response to service failure.

❖ **Share prices -** A share price is the price of a single share of a number of saleable stocks of a company, derivative or other financial asset.

❖ **Size of customer base -** It refers to the clients to whom a business sells products and services

❖ **Size of installed base –** It is a measure of the number of units of a particular type of product actually in use, as opposed to market share, which only reflects sales over a particular period.

❖ **Source of fill (also known as "fill source") -** It refers to where the material is obtained to fill a request when there are different tiers of suppliers.

❖ **Speed of innovation -** It refers to rate at which better solutions that meet new requirements, in-articulated needs or existing market needs are realised and contributes to better and faster innovation.

❖ **Stakeholder attitude -** It refers to the changes in attitude of designers, customers, suppliers and solution provider's attitude to that of pure manufacturing during transformation towards PSS.

❖ **Supplier reputation -** It refers to the level of reputation supplier have in the industry, which is assessed as supplier health by the customer before awarding contracts.

❖ **Supply chain visibility/ Information visibility -** It is the level of access to information by all the stakeholders. Information relating to common component failure types back to design, information on their sustaining engineering bills, their modification bills etc. could be shared. It overcomes the reliance on uncertain customer-supplied information.

❖ **Supply complexity -** For instance, the Tornado aircraft had some 350 separate contracts for the MoD team to manage. It refers to the complexity of relationships in the supply network induced when offering a combination of product and services.

❖ **Task complexity –** It refers to the objective characteristics of a task such as number of sub-tasks, requirement for specialised skills etc. It influences outsourcing decisions, when complex tasks are done better or cheaper by outside contractors.

❖ **Testing time –** It refers to time required for any installed product or system to be tested before and after repair or installation, to ensure the required safety standards etc. are met.

❖ **Training of the mechanic/ Training period/ Number of training sessions conducted -** It refers to the level of competence gained by the service personnel based on the training provided. As the product becomes more sophisticated, additional training for service personnel is necessary especially for diagnostic skills.

❖ **Transport system reliability/ Resource transition/Transport time -** It is the time allotted for transporting materials from the workstation where the preceding operation took place to the workstation where the current operation is to occur.

❖ **Type of service demanded –** It refers to whether it is a regular maintenance job or machine repair after a breakdown is demanded by the customer or enforced by the contractual obligations. Terms such as preventive maintenance, corrective maintenance and condition-based maintenance is also used.

❖ **Unexpressed customer demand -** It refers to the move from traditional demand for mass production to customised production or mass customisation, as value is added due to non-material aspect of products in PSS such as technological improvements, intellectual property etc.

❖ **Updates to documentation and training cost -** It is the cost incurred to provide training to the service personnel to upgrade their skill and knowledge level as well as the cost for generating new documentation to support the personnel to work with the new equipment, process etc.

❖ **Variation of the assets utilisation/ Change of usage patterns/ Utilisation rate of production machinery/ Equipment usage –** It refers to the time for which the equipment has been operational, for example, flying hours for aircraft.

❖ **Verification & Validation cost -** It typically involves simulation and testing of systems/subsystems which will cost-effectively and significantly improve the level of trust and the quality of products.

❖ **Warehouses and repair vendors location/ Proximity of spare parts -** The field facilities are located close to the customer's operations, as many of the service activities may need to be carried out on the customer's site. It also includes the proximity of spares to the field site.

❖ **Work card design -** A work card includes information about job type, job description details, estimated man-hours, job turn round time, spare parts and material requirements and tooling requirements. It facilitates improved communication through better document design.

❖ **Work force stability -** It is determined from the percentage of current employees with more than one year's service. Retention of experienced employees and reduction of employee turnover is significant in service sector.

Appendix D - Characterisation of Uncertainties

Characterisation is performed from the Level 1 supplier perspective (GeA) in the case study.

Table 15: Characterisation of Uncertainties Using Five Layer Classification

Characterisation Of Uncertainties Using Five Layer Classification					
Uncertainty	**Nature**	**Cause(Lack of understanding, Ambiguity, Human behaviour)**	**Level(Deterministic, Set, Interval, Ignorance)**	**Manifestation(Context, Data, Model, Phenomenological)**	**Expression (Quantitative, Qualitative)**
Availability of personnel	Epistemic	Lack of information; Inexperience; Human errors	Interval	Exogenous; Data (Incompleteness, Variation); Model (Mathematical, Computational)	Quantitative
Availability of spares (at level 1 supplier facility and customer facility)	Epistemic	Lack of understanding (Lack of information, Imprecision); Ambiguity (Conflicting evidence); Human behaviour (Human errors, Changes in personnel)	Set/ Interval	Endogenous/Exogenous; Data (Incompleteness, Inexactness, variation); Model (Mathematical, Computational); Phenomenological	Quantitative
Availability of test equipment	Epistemic	Lack of information; Human behaviour (Errors, Volition)	Set/ Interval	Endogenous; Data (Incompleteness, Variation); Model (Mathematical, Computational)	Quantitative
Availability of work bench	Epistemic	Lack of information	Set/ Interval	Endogenous; Data (Incompleteness, Variation); Model (Mathematical, Computational)	Quantitative
Customer damage	Epistemic, Aleatory	Lack of information; Ambiguity (Lack of definition, Conflicting evidence, Poor communication process)	Interval	Exogenous; Data (Incompleteness, Variation); Model (Mathematical, Computational)	Quantitative

Degree of contracting	Aleatory, Epistemic	Lack of understanding (Lack of information, Inexperience); Ambiguity (Lack of definition, Conflicting evidence)	Deterministic/Set	Endogenous/ Exogenous; Data (Inexactness, Variation); Model (Mathematical)	Qualitative/ Quantitative
Demand for contractor spares	Epistemic	Lack of understanding (Lack of information, Imprecision); Human behaviour (Error, Volition)	Interval	Exogenous; Data (Inexactness, Variation); Model (Computational)	Quantitative/ Qualitative
Demand for in-house spares	Epistemic	Lack of understanding (Lack of information, Imprecision); Human behaviour (Error, Volition)	Interval	Endogenous; Data (Inexactness, Variation); Model (Computational)	Quantitative/ Qualitative
Equipment readiness	Epistemic	Lack of information; Ambiguity (Lack of definition, Conflicting evidence); Human (error)	Deterministic/ Set	Exogenous; Data (Incompleteness); Model (Computational)	Quantitative
Equipment usage	Epistemic	Lack of understanding (Lack of information); Ambiguity (Lack of definition, Conflicting evidence), Human error	Interval	Exogenous; Data (Incompleteness, Inexactness, Variation); Model (Computational)	Quantitative
Failure rate	Epistemic	Lack of understanding (Lack of information); Ambiguity (Conflicting evidence); Human (errors)	Interval	Endogenous; Data (Variation); Model (Computational)	Quantitative
Infrastructural capability	Epistemic	Lack of understanding (Imprecision, Lack of information, Inexperience); Human (Changes in personnel)	Set	Exogenous; Data (Inexactness; Variation); Model (Conceptual; Mathematical)	Qualitative
Intellectual property	Epistemic/ Aleatory	Lack of understanding (Lack of information, Inexperience); Ambiguity	Deterministic/Set / Ignorance	Exogenous; Data (Variation, Inexactness); Model (Conceptual)	Qualitative

		(Vagueness, Poor communication process)			
Level of confidentiality	Epistemic/ Aleatory	Lack of understanding (Lack of information, Inexperience); Ambiguity (Vagueness, Poor communication)	Deterministic/ Set/ Ignorance	Exogenous; Data (Variation; , Inexactness Incompleteness); Model (Conceptual)	Qualitative
Level of skill and knowledge	Epistemic/ Aleatory	Lack of understanding (Imprecision, Lack of information, Inexperience); Ambiguity (Vagueness, Lack of definition, Conflicting evidence, Poor communication); Human (Volition, Changes in personnel, error)	Deterministic/ Set/ Interval	Endogenous; Data (Incompleteness); Model (Mathematical, Computational); Phenomenological	Qualitative/ Quantitative
No fault found	Epistemic	Lack of understanding (Imprecision, Inexperience); Ambiguity (Conflicting evidence, Poor communication); Human (Volition, Errors)	Set/Interval	Endogenous; Data (Inexactness, Variation); Model (Mathematical, Computational)	Qualitative/ Quantitative
Operating environment	Epistemic/ Aleatory	Lack of understanding (Lack of information); Ambiguity (Conflicting evidence, Poor communication)	Deterministic/Set	Exogenous; Data (Inexactness, Variation); Model (Mathematical, Computational); Phenomenological	Qualitative/ Quantitative
Production lead time	Epistemic	Lack of understanding (Imprecision, Inexperience); Human (Errors)	Set/ Interval	Endogenous; Data (Variation); Model (Mathematical, Computational)	Quantitative
Quality of support	Epistemic	Lack of understanding (Lack of information, Inexperience); Ambiguity (Conflicting evidence, Poor communication)	Set	Exogenous; Data (Inexactness, Variation); Model (Mathematical, Conceptual)	Qualitative
Remaining useful life	Epistemic/ Aleatory	Lack of understanding (Lack of information,	Interval	Endogenous; Data (Incompleteness); Model	Quantitative

		Inexperience); Human (Errors, Volition)		(Mathematical, Computational)	
Requisition wait time	Epistemic	Lack of understanding (Lack of information, Imprecision); Ambiguity (Conflicting evidence, Poor communication); Human volition	Set/ Interval	Exogenous; Data (Inexactness, Variation); Model (Mathematical, Computational)	Quantitative
Retrograde duration	Epistemic	Lack of information; Ambiguity (Poor communication, Conflicting evidence)	Interval	Exogenous; Data (Incompleteness, Inexactness, Variation); Model (Mathematical, Computational)	Quantitative
Safety stock	Epistemic	Lack of understanding (Lack of information, Inexperience); Ambiguity (Conflicting evidence, Poor communication)	Interval	Endogenous; Data (Inexactness, Incompleteness); Model (Mathematical, Computational)	Quantitative
Service demand	Epistemic/ Aleatory	Lack of understanding (Lack of information, Inexperience); Ambiguity (Conflicting evidence, Poor communication); Human (Volition)	Interval	Exogenous; Data (Variation); Model (Mathematical, Computational), Phenomenological	Quantitative
Service personnel efficiency	Epistemic/ Aleatory	Lack of understanding (Imprecision, Inexperience); Ambiguity (Lack of definition, Conflicting evidence); Human (Errors, Changes in personnel)	Set/ Interval	Endogenous; Data (Inexactness, Variation); Model (Mathematical, Computational); Phenomenological	Qualitative/ Quantitative
Supply chain visibility	Epistemic	Lack of understanding (Lack of information), Ambiguity (Lack of definition, Poor communication)	Set/ Interval	Exogenous; Data (Incompleteness, Inexactness, Variation); Model (Computational); Phenomenological	Qualitative/ Quantitative
Task complexity	Epistemic	Lack of understanding (Imprecision, Lack of information, Inexperience);	Set/ Interval	Endogenous; Data (Incompleteness, Inexactness; Variation);	Qualitative/ Quantitative

		Ambiguity (Vagueness, Lack of definition, Poor communication); Human (Volition, Error, Changes in personnel)		Model (Mathematical, Computational)	
Transport time	Epistemic	Lack of understanding (Imprecision); Ambiguity (Poor communication); Human (error)	Interval	Exogenous; Data (Inexactness, Variation); Model (Mathematical, Computational); Phenomenological	Quantitative
Turnaround time	Epistemic/ Aleatory	Lack of understanding (Imprecision, Inexperience); Ambiguity (Lack of definition); Human (Error)	Interval	Endogenous; Data (Inexactness, Variation); Model (Mathematical, Computational)	Quantitative

Table 16: Characterisation of Uncertainties Using Multi-Layer Classification

Characterisation Of Uncertainties Using Multi-Layer Classification							
Uncertainty	**Nature**	**Context**	**Decision Level**	**Scale Level**	**Effect**	**Cause**	**Source**
Availability of personnel	Mixture of epistemic & aleatory	Intra-organisation	Operational	Numerical	Manifest	Direct (eg. Direct influence on Turnaround time)	Resource/ Organisation
Availability of spares	Mixture of epistemic & aleatory	Inter/Intra organisation	Operational	Numerical	Manifest	Direct (eg. Direct influence on Turnaround time)	Resource/ Organisation/Procurement
Availability of test equipment	Mixture of epistemic & aleatory	Intra organisation	Operational	Numerical	Manifest	Direct (eg. Direct influence on Availability of work bench)	Resource/ Organisation/ Procurement
Availability of work bench	Epistemic	Intra-organisation	Operational	Numerical	Manifest	Direct (eg. Direct influence on Turnaround time)	Resource/ Infrastructure/ Procurement
Customer damage	Epistemic	Inter-organisation	Tactical/ Operational	Numerical	Manifest	Direct (eg. Direct influence on Failure rate)	Customer, Product

Degree of contracting	Aleatory	Inter-organisation/ Exogenous	Strategic/ Operational	Linguistic	Manifest	Direct (eg. Direct influence on Supply Chain Visibility)	Contract/ Organisation
Demand for spares(contractor/ in-house spares)	Epistemic	Inter-organisation/ Exogenous	Operational	Numerical	Manifest	Direct (eg. Direct influence on Availability of spares)	Product performance/Customer demand/ Macro-economic
Equipment readiness	Mixture of epistemic & aleatory	Inter-organisation/ Exogenous	Operational/ Tactical	Numerical	Manifest	Direct (eg. Direct influence on Mission readiness)	Product performance/ Contract/ Service process
Equipment usage	Epistemic	Inter-organisation/ Exogenous	Operational	Numerical	Manifest	Direct (eg. Direct influence on Failure rate)	Customer/ Contract/ Product
Failure rate	Mixture of epistemic & aleatory	Inter-organisation	Operational	Numerical	Manifest	Direct (eg. Direct influence on Service demand)	Product performance/Customer demand
Infrastructural capability	Mixture of epistemic & aleatory	Intra-organisation	Strategic/ Operational	Numerical	Manifest	Direct (eg. Direct influence on Infrastructural capability)	Organisation
Intellectual property	Epistemic	Inter-organisation	Strategic	Linguistic	Latent	Direct (eg. Direct influence on Service demand)	Contract/ Organisation
Level of confidentiality	Epistemic/ Mixture of epistemic and aleatory	Inter-organisation/ Exogenous	Strategic/ Tactical	Linguistic	Latent (partly manifest)	Direct (eg. Direct influence on Supply chain visibility)	Customer/ Supply chain/ Macro-economic
Level of skill & knowledge	Epistemic/ Mixture of epistemic and aleatory	Inter/ Intra-organisation	Operational	Linguistic/ Numerical	Manifest (partly latent)	Direct (eg. Direct influence on Service personnel efficiency)	Human / Product type/ Upgrades/ Process
No Fault Found (NFF)	Epistemic/ Mixture of epistemic and aleatory	Inter/ Intra-organisation	Operational	Numerical	Manifest	Direct (eg. Direct influence on Availability of spares)	Service process/ Product/ Customer
Operating environment	Epistemic/ Aleatory/ Mixture of epistemic and aleatory	Inter-organisation/ Exogenous	Operational	Linguistic/ Numerical	Manifest/ Latent	Direct (eg. Direct influence on Failure rate)	Customer
Production lead time	Mixture of epistemic and aleatory	Inter-Intra organisation	Strategic/ Operational	Numerical	Manifest	Direct (eg. Direct influence on Safety stock)	Manufacturing process/ Product type/ Supply chain

Quality of support	Epistemic/ Aleatory	Inter-organisation/ Exogenous	Tactical/ Operational	Linguistic	Latent	Direct (eg. Direct influence on Supply chain visibility)	Customer/ Supply Chain
Remaining useful life	Epistemic/ Mixture of epistemic & aleatory	Intra-organisation	Operational/ Strategic	Numerical	Manifest	Direct (eg. Direct influence on Failure rate)	Product type/ Customer
Requisition wait time	Epistemic	Inter-organisation	Operational	Numerical	Manifest	Direct (eg. Direct influence on Availability of spares_1)	Service process/ Hardware/ Supply chain
Retrograde duration	Epistemic	Inter-organisation/ Exogenous	Operational	Numerical	Manifest	Direct (eg. Direct influence on Service demand)	Customer/ Contract
Safety stock	Epistemic	Inter-organisation	Tactical/Operational	Numerical	Manifest	Direct (eg. Direct influence on Availability of spares_1)	Product performance/ Resource
Service personnel efficiency	Epistemic/ Mixture of epistemic and aleatory	Inter/ Intra-organisation	Operational	Linguistic/ Numerical	Manifest (partly latent)	Direct (eg. Direct influence on Turnaround time)	Human/ Product type/ Upgrades/ Service process
Service demand	Epistemic/ Mixture of aleatory and epistemic	Inter-organisation/ Exogenous	Operational/ Strategic	Numerical	Manifest	Direct (eg. Direct influence on Availability of spares_2 in BN)	Product/ Supply chain/ Customer
Supply chain visibility	Epistemic/ Mixture of epistemic and aleatory	Inter-organisation/ Exogenous	Strategic/ Tactical	Linguistic	Latent/ Manifest	Direct (eg. Direct influence on Requisition wait time)	Supply chain/ Customer
Task complexity	Epistemic/ Mixture of epistemic and aleatory	Intra-organisation	Operational	Linguistic/Numerical	Manifest/ Latent	Direct (eg. Direct influence on Service personnel efficiency)	Service process/ Human
Transport time	Epistemic	Inter-organisation	Operational	Numerical	Manifest	Direct (eg. Direct influence on Availability of spares_2)	Supply chain
Turnaround time	Epistemic	Inter-organisation/ Exogenous	Operational	Numerical	Manifest	Direct (eg. Direct influence on Availability of spares_2)	Service process/ Resource

Appendix E - Elicitation of Prior and Dependency Information

Table 17: Decision on Node type – Continuous or Discrete

Uncertainty	Scale Level	Discrete/ Continuous
Availability of personnel	Numerical	Continuous
Availability of spares	Numerical	Continuous
Availability of test equipment	Numerical	Continuous
Availability of work bench	Numerical	Continuous
Customer damage	Numerical	Continuous
Degree of contracting	Linguistic	Discrete
Demand for spares (contractor/ in-house spares)	Numerical	Continuous
Equipment readiness	Numerical	Continuous
Equipment usage	Numerical	Continuous
Failure rate	Numerical	Continuous
Infrastructural capability	Numerical	Continuous
Intellectual property	Linguistic	Discrete
Level of confidentiality	Linguistic	Discrete
Level of skill & knowledge	Linguistic	Discrete
No Fault Found (NFF)	Numerical	Continuous
Operating environment	Linguistic	Discrete
Production lead time	Numerical	Continuous
Quality of support	Linguistic	Discrete
Remaining useful life	Numerical	Continuous
Requisition wait time	Numerical	Continuous
Retrograde duration	Numerical	Continuous

Safety stock	Numerical	Continuous
Service personnel efficiency	Linguistic	Discrete
Service demand	Numerical	Continuous
Supply chain visibility	Linguistic	Discrete
Task complexity	Linguistic	Discrete
Transport time	Numerical	Continuous
Turnaround time	Numerical	Continuous

Elicitation Questions - Prior Probability Distribution

Table 18: Nodes and their Assumed Probability Distribution

Node	**Unit**	**Type Of Probability Distribution**	**Reason**	**Specification of PDF in Netica**
Availability of personnel	Percentage per month	Uniform Distribution	No preference stated	UniformDist (AvailabilityOfPersonnel, 30, 90)
Availability of spares_1	Percentage per month	Triangular Distribution	No preference stated	TriangularEnd3Dist (AvailabilityOfSpares_1, 80, 20,95)
Availability of spares_2	Percentage per month	Uniform Distribution	No preference stated	UniformDist(AvailabilityOfSpares_2, 30, 90)
Availability of test equipment	Percentage per month	Uniform Distribution	No preference stated	UniformDist(AvailabilityOfTestEquipment, 30, 90)
Availability of work bench	Percentage per month	Uniform Distribution	No preference stated	UniformDist(AvailabilityOfWorkBench, 30, 90)
Customer damage	MHDDs per year	Normal Distribution	Expert	NormalDist(CustomerDamage, 16.66, 10.67)
Equipment readiness	Percentage per year	Uniform Distribution	No preference stated	UniformDist(EquipmentReadiness, 30, 90)
Equipment usage	Hours/year	Normal Distribution	Expert	NormalDist(EquipmentUsage, 178.55, 127.54)
Failure rate	MHDDs/ month	Normal Distribution	Expert	NormalDist (FailureRate, 110, 6.20)

No Fault Found	MHDDs/ year	Normal Distribution	Best fit	NormalDist(NoFaultFound, 1.50, 0.31)
Production lead time	Months	Gamma Distribution	Expert	GammaDist (ProductionLeadTime, 23.22, 1.28)
Remaining useful life	Hours	Normal Distribution	Best fit	NormalDist(RemainingUsefulLife, 5317.18, 611.59)
Requisition wait time	Days	Lognormal Distribution	Expert	LognormalDist (RequisitionWaitTime, 0.77, 0.52)
Retrograde duration	Days	Lognormal Distribution	Expert	LognormalDist(RetrogradeDuration, 3.14, 0.95)
Safety stock	MHDDs/ month	Normal Distribution	Best fit	NormalDist (SafetyStock, 14.28, 10.20)
Service demand	MHDDs/ month	Lognormal Distribution	Expert	LognormalDist(ServiceDemand, 1.54, 0.55)
Transport time	Days	Lognormal Distribution	Expert	LognormalDist (TransportTime, 0.77, 0.52)
Turnaround time	Days	Lognormal Distribution	Expert	LognormalDist(TurnaroundTime, 3.17, 0.67)

Production lead time (PLT)

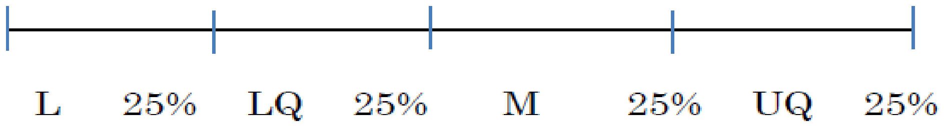
Q) Observing the production of 100 random MHDD's, what is the plausible lower bound (L) and upper bound (U) value for PLT?

Q) Can you determine a value (your median) such that PLT is equally likely to be less than or greater than this point?

Q) Suppose you were told that PLT is below your assessed median. Can you now determine a new value (lower quartile LQ) such that it is equally likely that E is less than or greater than this value?

Q) Suppose you were told that PLT is above your assessed median. Can you now determine a new value (upper quartile UQ) such that it is equally likely that E is less than or greater than this value?

Write the LQ and UQ values on the scale below



Requisition wait time (RWT)

Q) Assumption - Just in-time replenishment is the spares policy adopted for contractor supplied SRI.

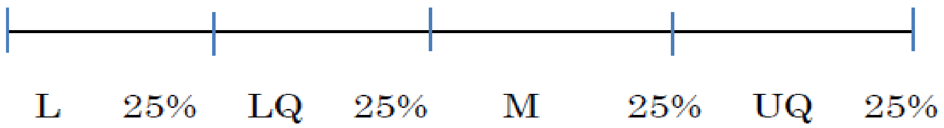
Observing 100 MHDD's ordered in a year, what is the typical time elapsed, when an order is placed to the time it is received?

Q) Can you determine a value (your median M) such that RWT is equally likely to be less than or greater than this point?

Q) Suppose you were told that RWT is below your assessed median. Can you now determine a new value (lower quartile LQ) such that it is equally likely that RWT is less than or greater than this value?

Q) Suppose you were told that RWT is above your assessed median. Can you now determine a new value (upper quartile UQ) such that it is equally likely that RWT is less than or greater than this value?

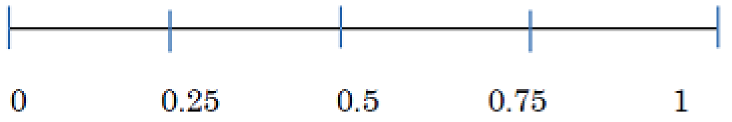
Write the LQ and UQ values on the scale below



Demand for Contractor and In-house spares

Q) Observing 100 MHDD breakdown rate in a typical month, where some modules are in-house produced and repaired and some modules shipped to the contractor for repair, what probability would you assign for the demand of In-house spares and demand for contractor supplied spares?

Write the probabilities for in-house spares demand and contractor spares demand per month on the probability scale below, taking care to put them in the most appropriate position between 0 and 1.



No Fault Found (NFF)

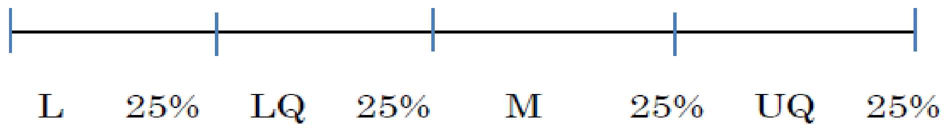
Q) Observing 100 MHDD breakdown rate in a typical month, a portion of which could be reported/tested as NFF, what is the plausible lower bound (L) and upper bound (U) values for NFF?

Q) Can you determine a value (your median M) such that NFF is equally likely to be less than or greater than this point?

Q) Suppose you were told that NFF is below your assessed median. Can you now determine a new value (lower quartile LQ) such that it is equally likely that NFF is less than or greater than this value?

Q) Suppose you were told that NFF is above your assessed median. Can you now determine a new value (upper quartile UQ) such that it is equally likely that NFF is less than or greater than this value?

Write the LQ and UQ values on the scale below



Safety Stock (SS)

Q) Observing 100 MHDD breakdown rate in a typical month, what is the plausible lower bound (L) and upper bound (U) values for SS that is maintained at the LEVEL 1 SUPPLIER inventory?

Q) Can you determine a value (your median M) such that SS is equally likely to be less than or greater than this point?

Q) Suppose you were told that SS is below your assessed median. Can you now determine a new value (lower quartile LQ) such that it is equally likely that SS is less than or greater than this value?

Q) Suppose you were told that SS is above your assessed median. Can you now determine a new value (upper quartile UQ) such that it is equally likely that SS is less than or greater than this value?

Write the LQ and UQ values on the scale below

L 25% LQ 25% M 25% UQ 25%

Task complexity (TC)

Q) Observing 100 MHDD repairs coming in, what probability would you assign for the values of low L, medium M and high H for variable TC?

Write the L, M and H on the probability scale below, taking care to put them in the most appropriate position between 0 and 1.

0 0.25 0.5 0.75 1

Level of skill & knowledge required (LSK)

Q) Observing 100 MHDD repairs coming in a month, what probability would you assign for the values of low L, medium M and high H for variable LSK required to perform the repair of MHDD?

Write the L, M and H on the probability scale below, taking care to put them in the most appropriate position between 0 and 1.

0 0.25 0.5 0.75 1

Availability of test equipment (ATE)

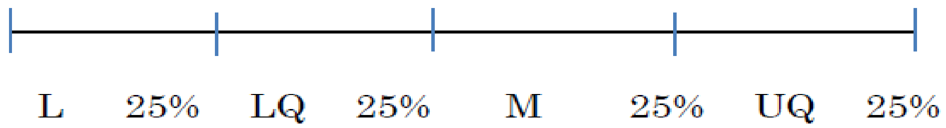
Q) Observing 100 MHDD repairs coming in a month, what is the minimal and maximal chance, a test equipment is available for use to repair the unserviceable MHDD?

Q) Can you determine a value (your median M) such that ATE is equally likely to be less than or greater than this point?

Q) Suppose you were told that ATE is below your assessed median. Can you now determine a new value (lower quartile LQ) such that it is equally likely that ATE is less than or greater than this value?

Q) Suppose you were told that ATE is above your assessed median. Can you now determine a new value (upper quartile UQ) such that it is equally likely that ATE is less than or greater than this value?

Write the LQ and UQ values on the scale below



Availability of spares at Level 1 supplier Facility (AS)

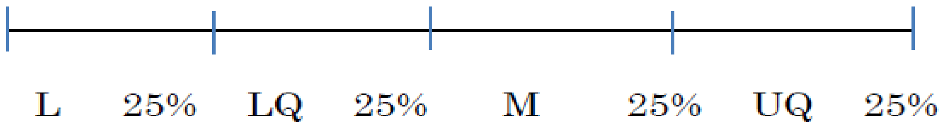
Q) Observing 100 MHDD repairs coming in a month, what is the minimal and maximal chance, a functional/working spare is available for use to repair the unserviceable MHDD?

Q) Can you determine a value (your median M) such that AS is equally likely to be less than or greater than this point?

Q) Suppose you were told that AS is below your assessed median. Can you now determine a new value (lower quartile LQ) such that it is equally likely that AS is less than or greater than this value?

Q) Suppose you were told that AS is above your assessed median. Can you now determine a new value (upper quartile UQ) such that it is equally likely that AS is less than or greater than this value?

Write the LQ and UQ values on the scale below



Availability of spares at Customer Facility (AS)

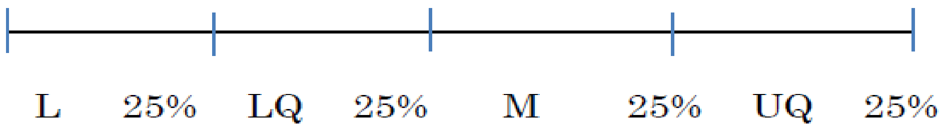
Q) Observing 100 MHDD repairs coming in a month, what is the minimal and maximal chance, a functional/working spare is available for use to repair the unserviceable MHDD?

Q) Can you determine a value (your median M) such that AS is equally likely to be less than or greater than this point?

Q) Suppose you were told that AS is below your assessed median. Can you now determine a new value (lower quartile LQ) such that it is equally likely that AS is less than or greater than this value?

Q) Suppose you were told that AS is above your assessed median. Can you now determine a new value (upper quartile UQ) such that it is equally likely that AS is less than or greater than this value?

Write the LQ and UQ values on the scale below



Equipment Readiness (ER)

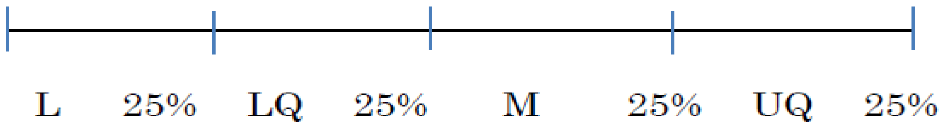
Q) what is the minimal and maximal percent of functional MHDDs' installed on RAF fleet that are fully mission capable in a month (year) ?

Q) Can you determine a value (your median M) such that ER is equally likely to be less than or greater than this point?

Q) Suppose you were told that ER is below your assessed median. Can you now determine a new value (lower quartile LQ) such that it is equally likely that ER is less than or greater than this value?

Q) Suppose you were told that ER is above your assessed median. Can you now determine a new value (upper quartile UQ) such that it is equally likely that ER is less than or greater than this value?

Write the LQ and UQ values on the scale below,



Customer damage (CD)

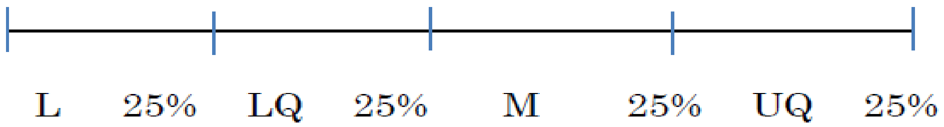
Q) Observing typical MHDD repairs coming in a year, what is the minimal and maximal chance, a MHDD breakdown is due to customer damage?

Q) Can you determine a value (your median M) such that CD is equally likely to be less than or greater than this point?

Q) Suppose you were told that CD is below your assessed median. Can you now determine a new value (lower quartile LQ) such that it is equally likely that CD is less than or greater than this value?

Q) Suppose you were told that CD is above your assessed median. Can you now determine a new value (upper quartile UQ) such that it is equally likely that CD is less than or greater than this value?

Write the LQ and UQ values on the scale below



Equipment usage (EU)

Q) Observing the usage of 100 MHDD's in hours, what is the plausible lower bound (L) and upper bound (U) values for EU for a year?

Q) Can you determine a value (your median M) such that EU is equally likely to be less than or greater than this point?

Q) Suppose you were told that EU is below your assessed median. Can you now determine a new value (lower quartile LQ) such that it is equally likely that EU is less than or greater than this value?

Q) Suppose you were told that EU is above your assessed median. Can you now determine a new value (upper quartile UQ) such that it is equally likely that EU is less than or greater than this value?

Write the LQ and UQ values on the scale below

Failure rate (FR)

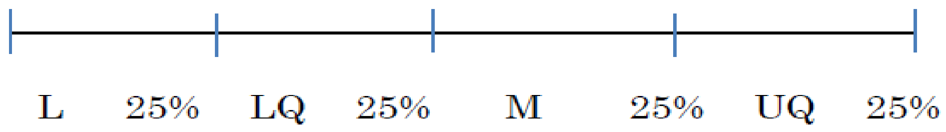
Q) Observing 100 MHDD's operated by RAF, what is the plausible lower bound (L) and upper bound (U) values for FR per month?

Q) Can you determine a value (your median M) such that FR is equally likely to be less than or greater than this point?

Q) Suppose you were told that FR is below your assessed median. Can you now determine a new value (lower quartile LQ) such that it is equally likely that FR is less than or greater than this value?

Q) Suppose you were told that FR is above your assessed median. Can you now determine a new value (upper quartile UQ) such that it is equally likely that FR is less than or greater than this value?

Write the LQ and UQ values on the scale below



Remaining useful life (RUL)

Q) Observing 100 MHDD's operated by RAF, what is the plausible lower bound (L) and upper bound (U) values for RUL at the current time?

Q) Can you determine a value (your median M) such that RUL is equally likely to be less than or greater than this point?

Q) Suppose you were told that RUL is below your assessed median. Can you now determine a new value (lower quartile LQ) such that it is equally likely that RUL is less than or greater than this value?

Q) Suppose you were told that RUL is above your assessed median. Can you now determine a new value (upper quartile UQ) such that it is equally likely that RUL is less than or greater than this value?

Write the LQ and UQ values on the scale below

Retrograde Duration (RD)

Q) Observing random unserviceable MHDD's sent to level 1 supplier for repair, what is the plausible lower bound (L) and upper bound (U) values for RD at the current time?

Q) Can you determine a value (your median M) such that RD is equally likely to be less than or greater than this point?

Q) Suppose you were told that RD is below your assessed median. Can you now determine a new value (lower quartile LQ) such that it is equally likely that RD is less than or greater than this value?

Q) Suppose you were told that RD is above your assessed median. Can you now determine a new value (upper quartile UQ) such that it is equally likely that RD is less than or greater than this value?

Write the LQ and UQ values on the scale below

Service Demand (SD)

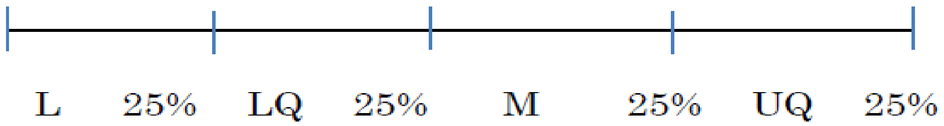
Q) Observing random unserviceable MHDD's sent to level 1 supplier for repair, what is the plausible lower bound (L) and upper bound (U) values for SD per month?

Q) Can you determine a value (your median M) such that SD is equally likely to be less than or greater than this point?

Q) Suppose you were told that SD is below your assessed median. Can you now determine a new value (lower quartile LQ) such that it is equally likely that SD is less than or greater than this value?

Q) Suppose you were told that SD is above your assessed median. Can you now determine a new value (upper quartile UQ) such that it is equally likely that SD is less than or greater than this value?

Write the LQ and UQ values on the scale below



Transport Time (TM)

Q) Observing random unserviceable MHDD's shipped to customer from level 1 supplier, what is the plausible lower bound (L) and upper bound (U) values for TM in days?

Q) Can you determine a value (your median M) such that TM is equally likely to be less than or greater than this point?

Q) Suppose you were told that TM is below your assessed median. Can you now determine a new value (lower quartile LQ) such that it is equally likely that TM is less than or greater than this value?

Q) Suppose you were told that TM is above your assessed median. Can you now determine a new value (upper quartile UQ) such that it is equally likely that TM is less than or greater than this value?

Write the LQ and UQ values on the scale below

Turnaround Time (TT)

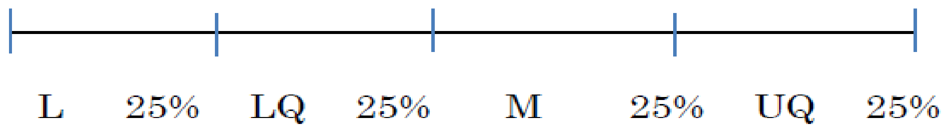
Q) Observing typical MHDD repairs coming in a year, what is the minimum and maximum time taken to repair the unserviceable MHDD including time for administrative time and shipping time?

Q) Can you determine a value (your median M) such that TT is equally likely to be less than or greater than this point?

Q) Suppose you were told that TT is below your assessed median. Can you now determine a new value (lower quartile LQ) such that it is equally likely that TT is less than or greater than this value?

Q) Suppose you were told that TT is above your assessed median. Can you now determine a new value (upper quartile UQ) such that it is equally likely that TT is less than or greater than this value?

Write the LQ and UQ values on the scale below



Dependency Assessment

Table 19: Type of Dependency Elicitation Method Used

Sub-network	**Dependency elicitation method**
Availability of personnel sub-network	Rank correlation method
Availability of spares (OEM) sub-network	Rank correlation method
Availability of spares (Customer) sub-network	Rank correlation method
Availability of work bench sub-network	Rank correlation method
Equipment readiness sub-network	Rank correlation method
Failure rate sub-network	Rank correlation method

Requisition wait time sub-network	Rank correlation method
Service personnel efficiency sub-network	Likelihood method
Service demand sub-network	Rank correlation method
Safety stock sub-network	Rank correlation method
Supply chain visibility sub-network	Likelihood method
Turnaround time sub-network	Rank correlation method

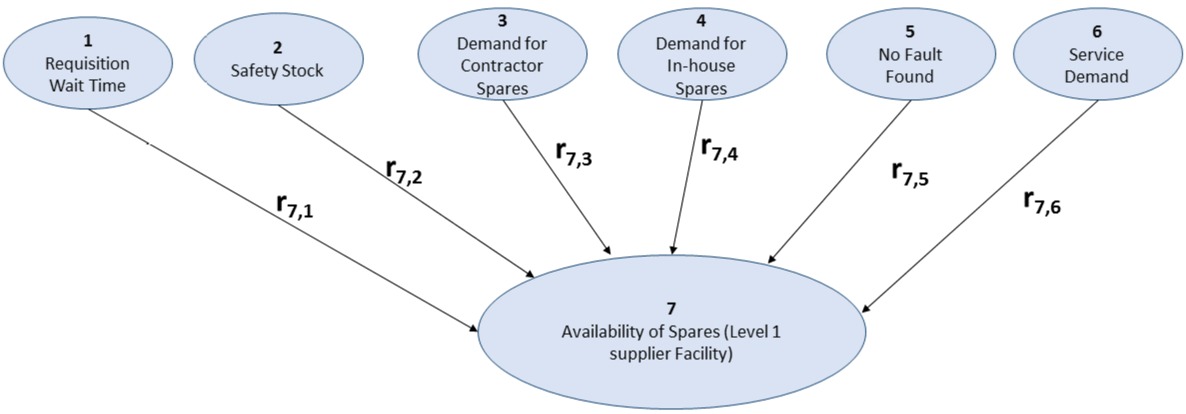
Table 20: Rank correlation values elicited for various dependencies between uncertainties.

Influencing factor/ Cause	Influenced factor/ Effect	Rank Correlation Value
Availability of personnel	Turnaround time	-0.3
Availability of spares	Turnaround time	-1
Availability of spares	Equipment readiness	0.85
Availability of test equipment	Availability of work bench	-0.25
Availability of work bench	Turnaround time	-0.3
Customer damage	Failure rate	0.7
Demand for contractor spares	Availability of spares	-0.85
Demand for in-house spares	Availability of spares	-0.45
Equipment usage	Failure rate	0.6
Failure rate	Service demand	0.95
Infrastructural capability	Service demand	-0.55
Intellectual property	Service demand	0.5
Level of skill & knowledge	Availability of personnel	-0.75
Level of skill & knowledge	Service personnel efficiency	0.9
No Fault Found	Availability of spares	-0.35
Operating environment	Failure rate	0.9
Production Lead Time	Safety Stock	-0.8
Remaining useful life (RUL)	Failure rate	-0.3
Requisition Wait Time	Availability of spares	-0.9
Retrograde duration	Service demand	0.8
Safety Stock	Availability of spares	0.7

Service demand	Availability of work bench	-0.75
Service Demand	Availability of spares (OEM facility)	-0.95
Service Demand	Availability of personnel	-0.85
Service personnel efficiency	Turnaround time	-0.1
Task complexity	Availability of personnel	-0.5
Task complexity	Service personnel efficiency	-0.5
Transport time	Availability of spares	-0.4
Turnaround time	Availability of spares	-0.85

*Sub-networks have been labelled using the child node name.

1) Availability of spares Sub-Network *



Q) What would you estimate for the correlation ($r_{7,1}$) between Requisition wait time (1) and Availability of Spares (7) on the scale below?

-1strong negative 0 no dependence +1 strong positive

Q) What would you estimate for the correlation ($r_{7,\,2}$) between Safety Stock (2) and Availability of Spares (7) on the scale below?

-1strong negative 0 no dependence +1 strong positive

Q) What would you estimate for the correlation ($r_{7,\,3}$) between Demand for contractor spares (3) and Availability of Spares (7) on the scale below?

-1strong negative 0 no dependence +1 strong positive

Q) What would you estimate for the correlation ($r_{7,4}$) between Demand for in-house spares and Availability of Spares (7) on the scale below?

-1 strong negative 0 no dependence +1 strong positive

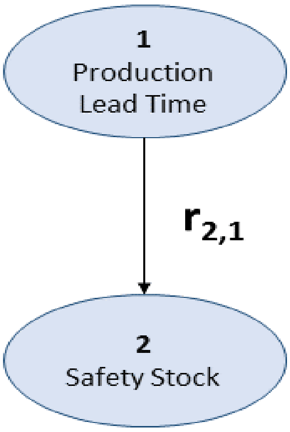
Q) What would you estimate for the correlation ($r_{7,5}$) between No Fault Found (5) and Availability of Spares (7) on the scale below?

-1 strong negative 0 no dependence +1 strong positive

Q) What would you estimate for the correlation ($r_{7,6}$) between Service demand (6) and Availability of Spares (7) on the scale below?

-1 strong negative 0 no dependence +1 strong positive

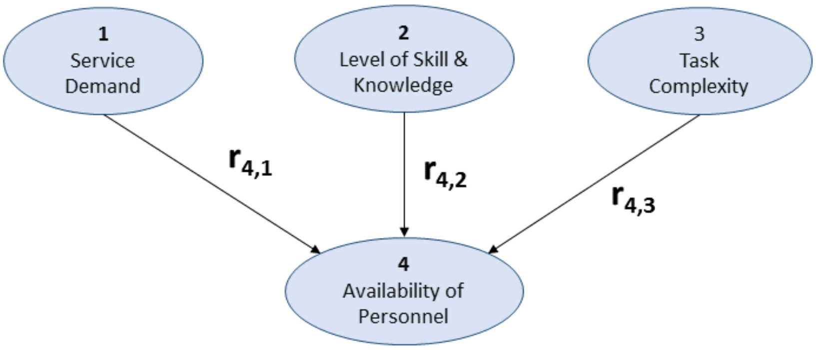
2) Safety stock Sub-Network



Q1) What would you estimate for the correlation ($r_{2,1}$) between Production Lead Time (1) and Safety Stock (2)?

-1 strong negative 0 no dependence +1 strong positive

3) Availability of personnel Sub-Network



Q) What would you estimate for the correlation ($r_{4,1}$) between Service Demand (1) and Availability of Personnel (4)?

-1 strong negative 0 no dependence +1 strong positive

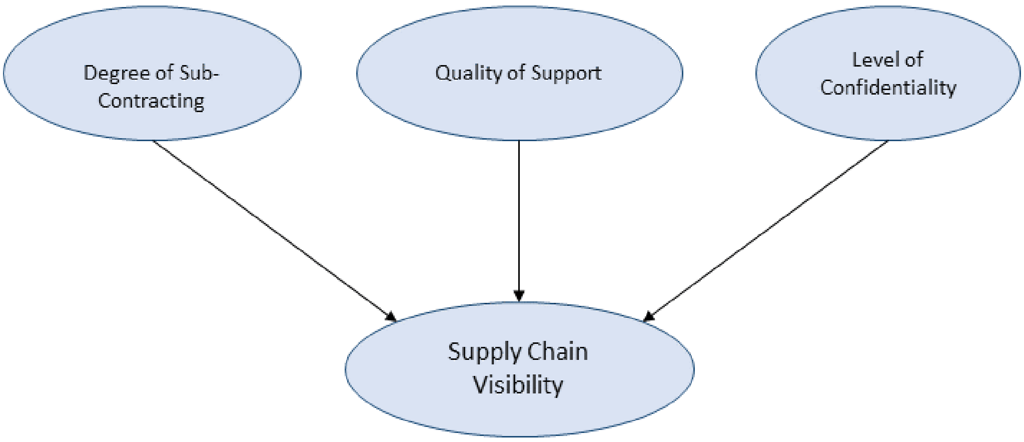
Q) What would you estimate for the correlation ($r_{4,2}$) between Level of Skill & Knowledge (2) and Availability of Personnel (4)?

-1 strong negative 0 no dependence +1 strong positive

Q) What would you estimate for the correlation ($r_{4,3}$) between Task complexity (3) and Availability of Personnel (4)?

-1 strong negative 0 no dependence +1 strong positive

4) Supply chain visibility Sub-Network

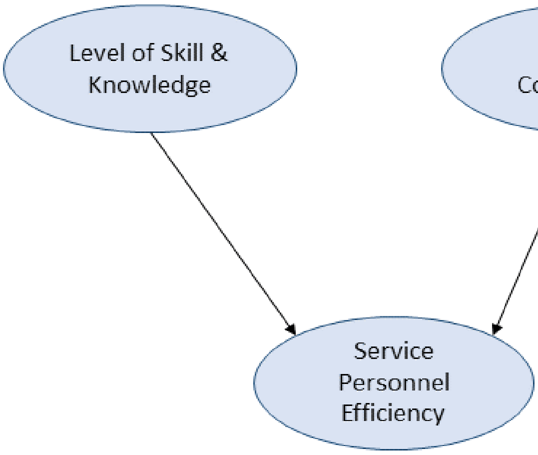


Assuming the child node has a prior distribution, where Low=0.33, Medium=0.34 and High=0.33 and base factor=2.

How much influence the different parent nodes might have on the possible outcomes for the child node?

Parent nodes	**Weighting factor**		
	Low	**Medium**	**High**
Level of Confidentiality			
Degree of Sub-Contracting			
Quality of Support			

5) Service personnel efficiency Sub-Network

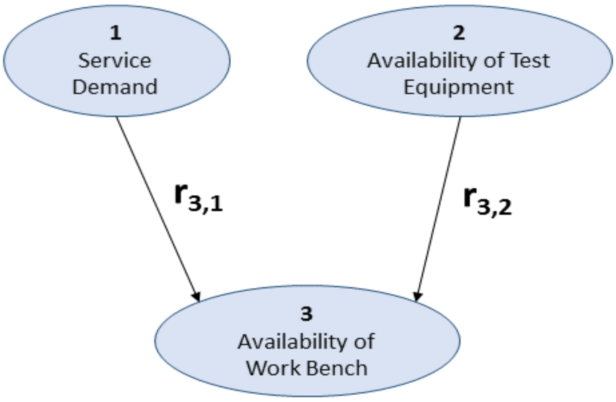


Assuming the child node has a prior distribution, where Low=0.33, Medium=0.34 and High=0.33 and base factor=2.

How much influence the different parent nodes might have on the possible outcomes for the child node?

Parent nodes	**Weighting factor**		
	Low	**Medium**	**High**
Level of Skill & Knowledge			
Task Complexity			

6) Availability of work bench Sub-Network



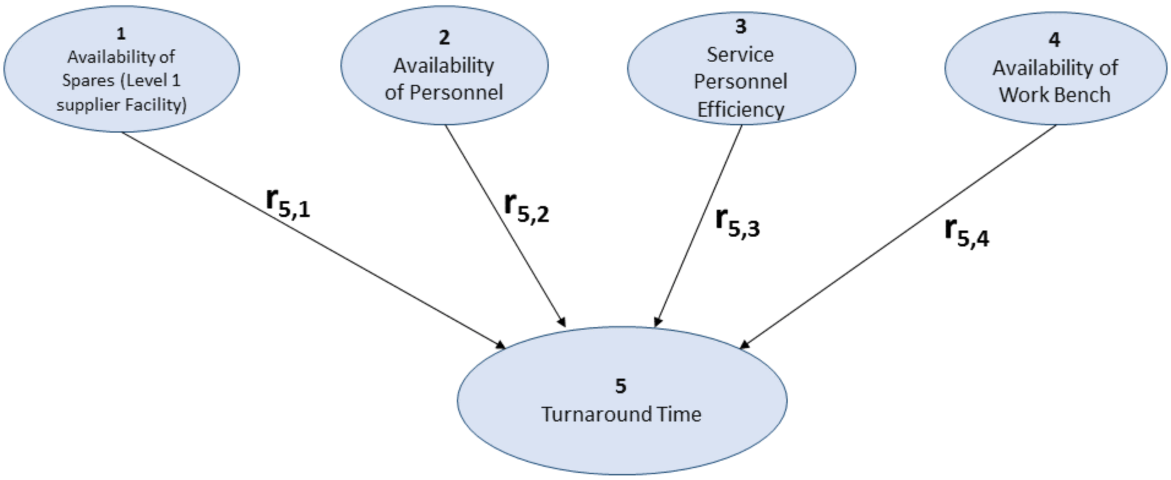
Q) What would you estimate for the correlation ($r_{3,1}$) between Service Demand (1) and Availability of Workbench (3)?

-1 strong negative 0 no dependence +1 strong positive

Q2) What would you estimate for the correlation ($r_{3,2}$) between Availability of Test Equipment (2) and Availability of Workbench (3)?

-1 strong negative 0 no dependence +1 strong positive

7) Turnaround time Sub-Network



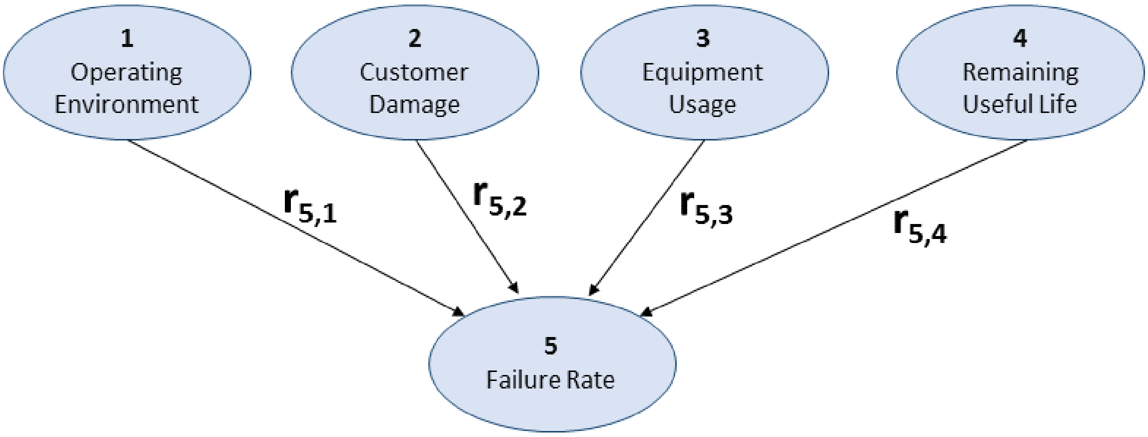
Q) What would you estimate for the correlation ($r_{5,1}$) between Availability of Spares (1) and Turnaround Time (5)?

Q) What would you estimate for the correlation ($r_{5,2}$) between Availability of Personnel (2) and Turnaround Time (5)?

Q) What would you estimate for the correlation ($r_{5,3}$) between Service Personnel Efficiency (3) and Availability of Spares (5) on the scale below?

Q) What would you estimate for the correlation ($r_{5,4}$) between Availability of Work Bench (4) and Turnaround Time (5)?

8) Failure rate Sub-Network



Q) What would you estimate for the correlation ($r_{5,1}$) between Operating Environment (1) and MHDD failure rate (5)?

-1 strong negative 0 no dependence +1 strong positive

Q) What would you estimate for the correlation ($r_{5,2}$) between Customer damage(2) and MHDD failure rate (5)?

-1 strong negative 0 no dependence +1 strong positive

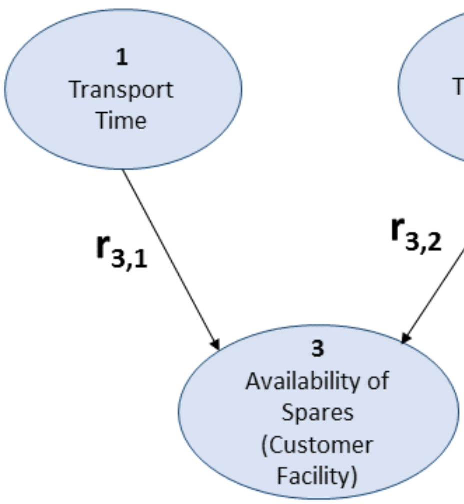
Q) What would you estimate for the correlation ($r_{5,3}$) between Equipment Usage (3) and MHDD failure rate (5)?

-1 strong negative 0 no dependence +1 strong positive

Q) What would you estimate for the correlation ($r_{5,4}$) between Requisition Useful Life (4) and MHDD failure rate (5)?

-1 strong negative 0 no dependence +1 strong positive

9) Availability of spares Sub-Network

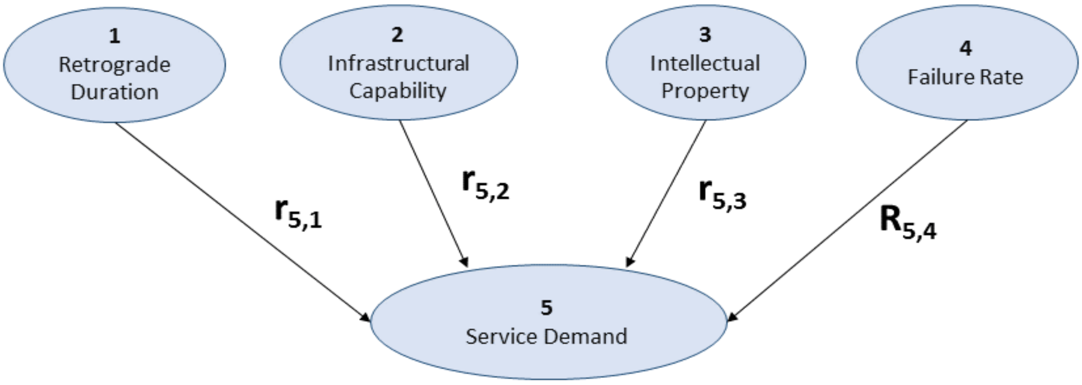


Q) What would you estimate for the correlation ($r_{3,1}$) between Transport Time (1) and Availability of Spares (3)?

Q2) What would you estimate for the correlation ($r_{3,2}$) between Turnaround Time (2) and Availability of Spares (3)?

-1 strong negative 0 no dependence +1 strong positive

10) Service demand Sub-network



Q) What would you estimate for the correlation ($r_{5,\,1}$) between Retrograde Time (1) and Service Demand (5)?

-1 strong negative 0 no dependence +1 strong positive

Q) What would you estimate for the correlation ($r_{5,\,2}$) between Infrastructural Capability (2) and Service Demand (5)?

-1 strong negative 0 no dependence +1 strong positive

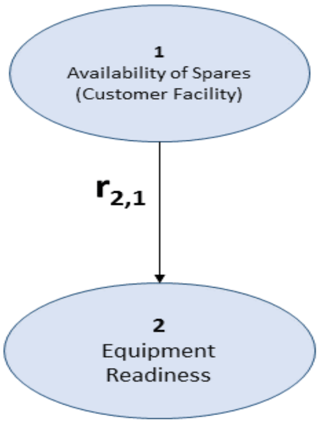
Q) What would you estimate for the correlation ($r_{5,3}$) between Retention of Intellectual Property (3) and Service Demand (5)?

-1 strong negative 0 no dependence +1 strong positive

Q) What would you estimate for the correlation ($r_{5,\,4}$) between MHDD Failure rate (4) and Quantity of unserviceable MHDD (5)?

-1 strong negative 0 no dependence +1 strong positive

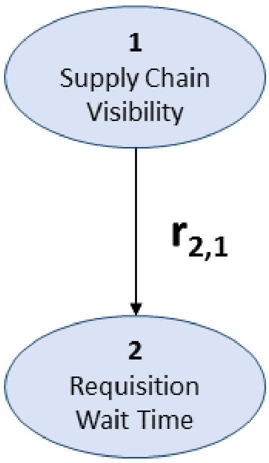
11) Equipment readiness Sub-network



Q) What would you estimate for the correlation ($r_{2,1}$) between Availability of Spares (1) and Equipment Readiness (2)?

-1 strong negative 0 no dependence +1 strong positive

12) Requisition wait time Sub-network



Q) What would you estimate for the correlation ($r_{2,1}$) between Supply Chain Visibility (1) and Requisition Wait Time (2)?

-1 strong negative 0 no dependence +1 strong positive

Support Material – Rank Correlation Method

The support material has content primarily taken from the website - https://www.mathsisfun.com/data/correlation.html

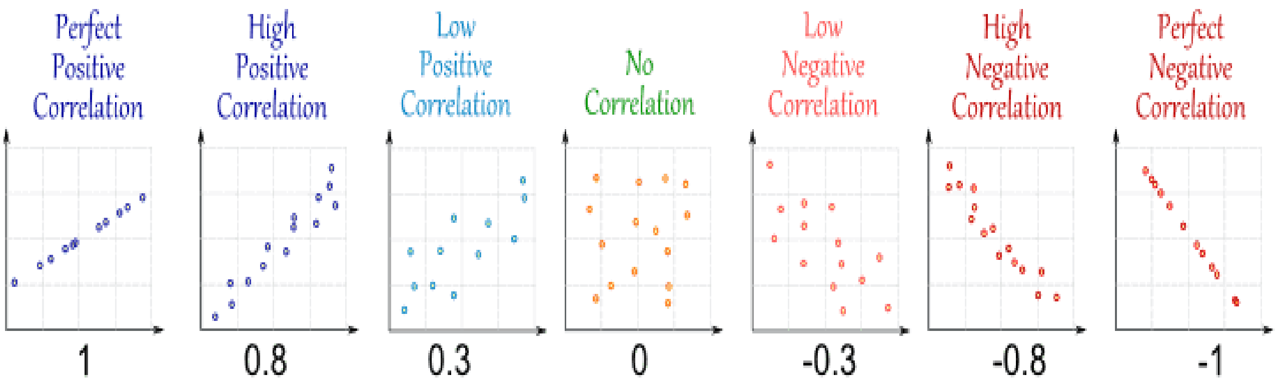
Rank Correlation

When the two sets of data are strongly linked together we say they have a **High Correlation**.

The word Correlation is made of **Co-** (meaning "together"), and **Relation**

- Correlation is **Positive** when the values **increase** together, and
- Correlation is **Negative** when one value **decreases** as the other increases

Like this:



Correlation can have a value:

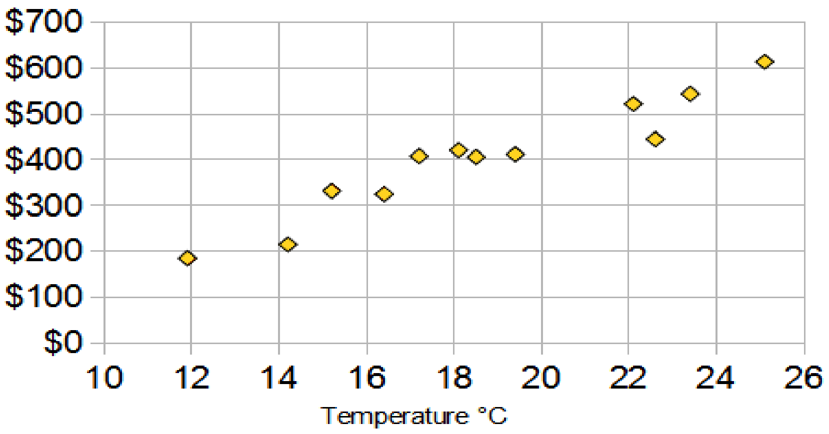
- 1 is a perfect positive correlation
- 0 is no correlation (the values don't seem linked at all)
- -1 is a perfect negative correlation

Example: Ice Cream Sales – Positive Correlation

The local ice cream shop keeps track of how much ice cream they sell versus the temperature on that day, here are their figures for the last 12 days:

Ice Cream Sales vs Temperature	
Temperature °C	Ice Cream Sales
14.2°	$215
16.4°	$325
11.9°	$185
15.2°	$332
18.5°	$406
22.1°	$522
19.4°	$412
25.1°	$614
23.4°	$544
18.1°	$421
22.6°	$445
17.2°	$408

And here is the same data as a Scatter Plot:



You can easily see that warmer weather leads to more sales, the relationship is good but not perfect.

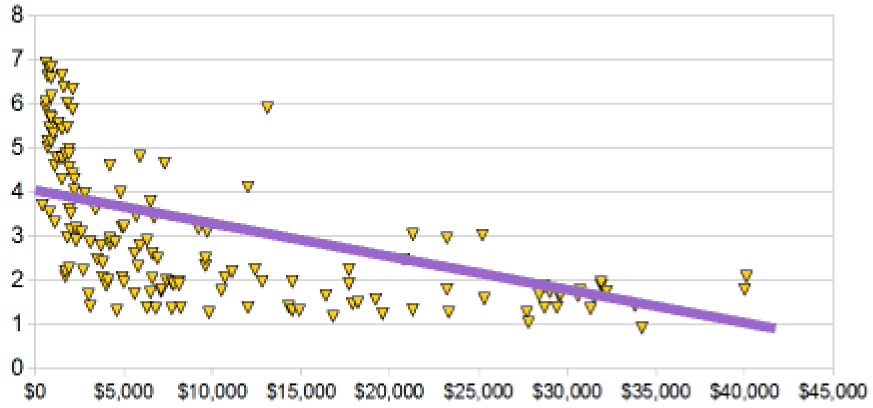
Example: Birth Rate vs Income - Negative Correlation

Correlations can be negative, which means there **is** a correlation but one value goes down as the other value increases.

The birth rate tends to be lower in richer countries.

Below is a scatter plot for about 100 different countries

Country	Yearly Production per Person	Birth Rate
Madagascar	$800	5.70
India	$3,100	2.85
Mexico	$9,600	2.49
Taiwan	$25,300	1.57
Norway	$40,000	1.78



It has a **negative correlation** (the line slopes down)

Appendix F – Sensitivity Analysis and Scenario Analysis

Sensitivity Analysis

Table 21: Change in Belief When Turnaround time=30 days on other uncertainties in the BN

Uncertainties and node states	Change in belief (Turnaround time=30 days)
Availability Of Spares_1	
20 to 30	0.079966
30 to 40	0.21781
40 to 50	0.32052
50 to 60	0.36522
60 to 70	0.01389
7O to 80	8.8286e-06
80 to 90	0.00017655
90 to 100	0.0024069
Service Demand	
0.438522 to 4	0.0067346
4 to 7	0.46126
7 to 55.135	0.532
Availability Of Spares_2	
30 to 40	0.44296
40 to 50	0.30871
50 to 60	0.1674
60 to 70	0.064117
70 to 80	0.015918
80 to 90	0.00089495
90 to 100	1.4345e-08
Failure Rate	
3 to 105	0.0056207
105 to 110	0.14842
110 to 115	0.38747
115 to 291	0.45849
Availability Of Personnel	
30 to 40	0.35903
40 to 50	0.26982
50 to 60	0.18996
60 to 70	0.1 191 1
70 to 80	0.052828
80 to 90	0.009256
90 to 100	5.7247e-08

Scenario Analysis

Table 22: Values suggested by MPE for other nodes in the BN

Nodes	States for Most Probable Explanation
Availability Of Personnel	80 to 90
Availability Of Spares_1	70 to 80
Availability Of Spares_2	80 to 90
Availability Of Test Equipment	30 to 40
Availability Of WorkBench	80 to 90
Customer Damage	-35.564 to 5
Degree Of Contracting	High
Demand For Contractor Spare	Medium
Demand For Inhouse-Spare	Low
Equipment Usage	-370.355 to 100
Failure Rate	3 to 105
Infrastructural Capability	High
Intellectual Property	Medium
Level Of Confidentiality	High
Level Of Skill & Knowledge	Low

No Fault Found	1 to 53
Operating Environment	Training
Production Lead Time	0.73 to 14
Quality Of Support	Low
Remaining Useful Life	5500 to 8011
Requisition Wait Time	4 to 21.39
Retrograde Duration	0.31 to 95
Safety Stock	24 to 59.99
Service Demand	0.44 to 4
Service Personnel Efficiency	Low
Supply Chain Visibility	Low
Task Complexity	Medium
Transport Time	0.21 to 3

Table 23: Change in Beliefs on Entering Findings for Supply chain visibility and Demand for contractor spares

Uncertainties	Initial Compiled States	After entering Findings for Supply chain visibility and Demand for contractor spares as low (L) and high (H) respectively	After entering Findings for Supply chain visibility and Demand for contractor spares as high (H) and low (L) respectively
Supply chain visibility	L=36.5 M=27	L=100	H=100

	H=36.5		
Demand for contractor spares	L=33.4 M=33.2 H=33.4	H=100	L=100
Turnaround time (TT)	106 ± 130	130 ± 140 P(TT<32) = 49%	99.4 ± 13 P(TT<32) = 62.7%

Table 24: Change in Beliefs on Entering Findings for Infrastructural Capability and Maintaining Favourable States for other Nodes (*Requisition wait time*, *Safety stock*, *Availability of spares_1*, *Availability of personnel* and *Availability of workbench)*

Uncertainties	Initial Compiled States	After entering findings for Infrastructural capability as low (L) and maintaining favourable states for other nodes	After entering findings for Infrastructural capability as High (H) and maintaining favourable states for other nodes
Infrastructural capability	L=36.5 M=27 H=36.5	L=100	H=100
Demand for contractor spares	L=33.4 M=33.2 H=33.4	L=100	L=100
Demand for in-house spares	L=33.4 M=33.2 H=33.4	L=100	L=100
Availability of personnel	60 ± 17	70-80%	70-80%
Service personnel efficiency	L=33.3 M=33.3 H=33.4	M=100	M=100
Availability of workbench	60 ± 17	70-80%	70-80%
Requisition wait time	6.65 ± 6.1	2-3	2-3
Safety stock	12.4 ± 21	42 ± 10	42 ± 10
Turnaround time (TT)	106 ± 30	21.2 ± 37	20.3 ± 33

Table 25: Change in Beliefs on Entering Findings for Turnaround time and Demand for In-House Spares

Uncertainties	Initial Compiled States	After entering findings for Turnaround time and Demand for in-house spares
Demand for in-house spares	L=33.4 M=33.2 H=33.4	H=100
Turnaround time	106 ± 130	30
Safety stock	12.4 ± 21	13.9 ± 19

Table 26: Change in Beliefs on Entering Findings for Retrograde duration and Customer damage

Uncertainties	Initial Compiled States	After entering findings for Retrograde duration	After entering findings for Customer damage	After entering findings for Retrograde duration and Customer damage
Retrograde duration	148 ± 430	95 to 2945	-	95 to 2945
Customer damage	16 ± 18	-	30 to 66	30 to 66
Turnaround time	106 ± 130	142 ± 140	141 ± 140	176 ± 140

Table 27: Change in Beliefs on Entering Findings for Turnaround time and Demand for in-house spares

Uncertainties	Initial Compiled States	After entering finding for Operating environment	After entering finding for Equipment usage	After entering findings for Operating environment and Equipment usage
Operating environment	Training Combat	Combat	-	Combat
Equipment usage	161 ± 230	-	>300	>300
Turnaround time	106 ± 130	159 ± 140	124 ± 140	179 ± 140