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A Value-Focussed Decision Framework for Manufacturing Research Environments

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Abstract. Industrial research centres have a requirement to deliver new products, technologies and processes which can be applied in manufacturing environments. The dynamic nature of these centres has attracted a growing need from industry for value-focussed decision based systems to be in place that include accurate and reliable cost estimation techniques. A holistic solution which is able to manage the dynamic and complex nature of knowledge within these environments is required. This paper offers the potential to provide a solution for a value-focussed cost estimation and decision framework capable of supporting technology selection within these environments.

Keywords. Cost engineering, decision making, uncertainty.

Introduction

To successfully mature a technology to full production requires significant investment in research and development, which must be optimally managed within the technology planning process [1]. The Manufacturing Capability Readiness Level (MCRL) system provides a rigorous gate review structure to ensure consistent process quality throughout development programmes. Stages 3-6 are the pre-production stages in which a technology is proven for production and requires significant R&D investment. These stages are particularly difficult to traverse as funding for R&D is less readily available than earlier stages and the technological challenges involved in maturing the technologies to a commercial scale are significant. The ‘valley of death’ idiom is used, in manufacturing environments, to reflect this difficulty, describing a valley in which technologies “die” before they are fully implemented [2]. The high value catapult centres have been designed to address this problem by providing industry with facilities and expertise needed to establish their technologies before they are scaled up to full production, thus reducing the risk to industry.

The major challenge in pre-production is the magnitude of uncertainty surrounding novel technologies; this can significantly affect the confidence in decision making.

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1. Background

1.1. Technology development

The dynamic and uncertain nature of technology maturity costs time and money and complicates decision making. Improved knowledge management, identification of cost drivers and appropriately informing the direction of R&D within the pre-production stages has the potential to address these issues. As illustrated in Figure 1, the R&D investment could be reduced and financial returns could be greater and achieved sooner. Providing decision makers in these environments with transparent, well- defined knowledge from historical, current and evolving sources of both qualitative and quantitative data could achieve this. Moreover the more detailed knowledge provided by this approach has the potential to be projected backwards to influence academic research.

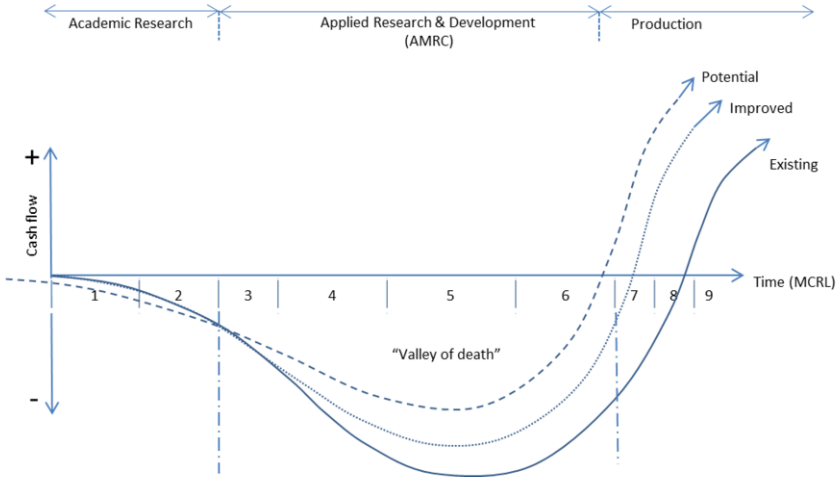

Figure 1. Traversing the "valley of death", adapted from [2].

1.2. Knowledge management

The task of developing a suitable means of managing knowledge which can be in many forms and residing in many places is particularly complex.

Knowledge evolves, with the value of information increasing, from raw data capture to processed and synthesised data that is able to support informed decisions. All forms of knowledge are present to varying degrees in industrial research centres and the specific requirements for elicitation and management need to be addressed to enable the most effective decisions to be made.

The types of knowledge that are required for value based decisions are described in Table 1. Value-focussed decision making resides in the discipline of cost engineering; the state of the art and limitations of existing methods is discussed in the next section.

1.3. Cost Engineering

Cost engineering refers to the application of scientific principles and techniques to solve a variety of cost related problems. The practice is carried out throughout the project life-cycle using cost models, tools and databases, whilst employing expert judgement concerning the specifics of the activity of interest. Often the output of cost engineering is the input to a decision making process [3].

Table 1. Knowledge requirements for value-focussed decision framework.

Title	Type	Description	The role of knowledge management
Cost estimates	Quantitative	Time Cost rates Resource requirements Depreciation Fixed and variable costs	Causal relationships Uncertainty Variability Normalisation Units
Capability and maturity data	Quantitative & Qualitative	MCRL Performance data.	
Expert opinion	Qualitative	Lessons learned Estimates.	Requires codification

Cost engineering methods span many industry sectors [4]–[6]. It is well known that targeting cost reduction in early stages of product design is beneficial [7]–[9]. However, very few publications specifically target cost during the early stages of R&D. Methods compare alternative designs, processes and, to a lesser extent, technologies [5], [10] but do not offer a value-based decision making solution for identifying where technology research and development opportunities exist.

Cost modelling maps a product (or process) parameter (or feature) to an economic value [11], [12]. The method is used to determine cost drivers and their sensitivities.

A distillation of the cost engineering literature indicates good practices relevant to the development of the proposed framework:

1. Definitions of cost and value must be agreed [13].
2. Data must be classified and centrally stored to enable knowledge sharing, sensitivity analysis and updating to occur [14], [15].
3. Methods to capture, represent and manage uncertainty is vital [16]-[18].
4. Cost estimation methods depend on the level of detail available [12], [17].
5. Feedback loops enable experts' knowledge to inform decisions [15], [19].
6. Stakeholder thinking and knowledge elicitation techniques reduce the likelihood of bias disrupting the accuracy of the data [20],[21].
7. Cost management systems must be aligned with the current governance [5], [22].

Research gaps identified in a review of cost engineering in the UK are summarised in Table 2.

The prominence of uncertainty and knowledge management related research in this list may signify the difficulties in managing the effect that these aspects can have on the accuracy of cost estimation and so further research will attempt to provide insight into these aspects.

An appreciation of the range of stakeholders holding this knowledge and influencing and driving the industrial requirements is essential for improved decision making and will be discussed in more detail.

1.4. Stakeholder management

The stakeholders not only influence decisions but in many cases provide the knowledge that is required to make those decisions.

Stakeholder analysis can be used to determine the level of interest and influences, views, and expectations of all stakeholders as well as determining where the most valuable knowledge resides. This information is captured within a gated project-review process [23] in centres like the one described. A stakeholder analysis matrix can be used to map and manage each stakeholder's level of support and influence [24].

This paper illustrates that to satisfy the requirement for a robust cost engineering framework, a thorough understanding of the complexities in decision making, combined with a way to manage the uncertainties and knowledge, is essential. Using observational methods to diagnose the context and purpose, as well as insights from literature, a conceptual framework is created to demonstrate the theoretical structure of research ideas and concepts for value-focussed decision making.

Table 2. Research gaps in cost enginering [7].

Gaps in engineering research	
Managing uncertainty	A framework for capturing critical uncertainties that impact life cycle costing
	Consideration of aleatory and epistemic uncertainties separately
	Approaches for the qualitative affordability factors
	Trade-offs between customer affordability and manufacturer profitability
	Recognition of uncertainty throughout the life-cycle
	Improved understanding of uncertainty variation through the full life cycle
	Verification and validation of epistemic uncertainties in cost estimation
	More representative LCC model
Knowledge management	Quantitative & Qualitative
Design stage	Qualitative

2. Methodology

This work represents the first stage in a research initiative which aims to establish a link between value-related knowledge management and improved decision making in environments with significant uncertainty. The nature of the research setting is complex. The environment spans internal and external boundaries. The drivers and knowledge required to make cost effective decisions are uncertain and dynamic, and significantly affect the confidence in decision making.

The wider research study is a four year EPSRC and Rolls-Royce Plc funded Engineering Doctorate which aims to:

"Develop, implement and evaluate a framework for value-focussed technology selection, for use in advanced manufacturing research and development."

The aims will be met by the following objectives:

- To identify the stakeholders and their requirements;
- To identify and elicit the extant quantitative and qualitative knowledge, and interrelationships;

- To identify the most suitable methods for handling uncertainty, changing information, and to support decision making;
- To develop and validate the framework, using two case studies, from different phases of the technology readiness scale.

2.1. Mixed methods research

The research aim for this study includes the analysis of quantitative cost data and qualitative insight from experts and is aiming to synthesise both in a way to support decision making. In this regard it lends itself to mixed methods research [25]. Mixed methods can combine approaches, methods, data and types of analysis [26].

3. Preliminary results and discussion

3.1. Contextual model

To gain further insight into the significance of these complexities within applied manufacturing R&D, a piece of exploratory research was conducted on a representative project from the Advanced Manufacturing Research Centre (AMRC). The aim of the project was to determine the most appropriate tooling for the machining of a novel material. The requirement originated from the driver to reduce the weight of an aircraft. Significant investment is required to establish new manufacturing regimes and so experts at the AMRC were employed to identify the most cost efficient solution. The flow and complexities of knowledge management throughout the project were elicited using semi-structured interviews and captured in a conceptual model (Figure 2).

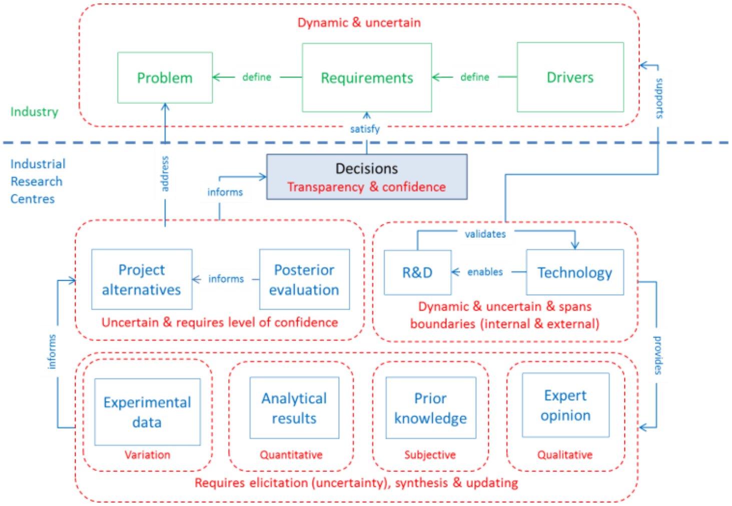

Figure 2. Conceptual model of decision making in manufacturing R&D.

The experts had to draw from existing data and knowledge, as well as conduct R&D to evaluate a set of alternative solutions to the problem. This evaluation was complex due to the requirements in elicitation and management of knowledge as well as the uncertainty which can influence the confidence in the alternatives provided to the customer. When compared to the findings from the knowledge base there are clear synergies in terms of considerations for decision making.

3.2. Conceptional framework for value-focussed decision making

To consolidate the findings from the knowledge base, the model of decision making, and from discussions with stakeholders, a conceptual framework has been developed (Figure 3). The framework breaks down the challenge into three areas: (1) Input - the elicitation of knowledge and to provide a contextual understanding; (2) Process - data consolidation, modelling and analysis; (3) Output - communication and integration of the framework to support decision making. The learning outcomes are then fed back into the framework for updating to occur. The sequence of activities that an organisation could adopt to improve industrial R&D decision making is sketched below:

- **Elicit** and represent existing cost related knowledge including the uncertainties in this knowledge;
- **Consolidate** this knowledge by synthesising the sources of data, building models and mapping the interrelationships;
- **Analyse** the models using interrogation techniques such as sensitivity analysis to determine the drivers;
- **Communicate** the knowledge and uncertainties in a way useful for decision making.

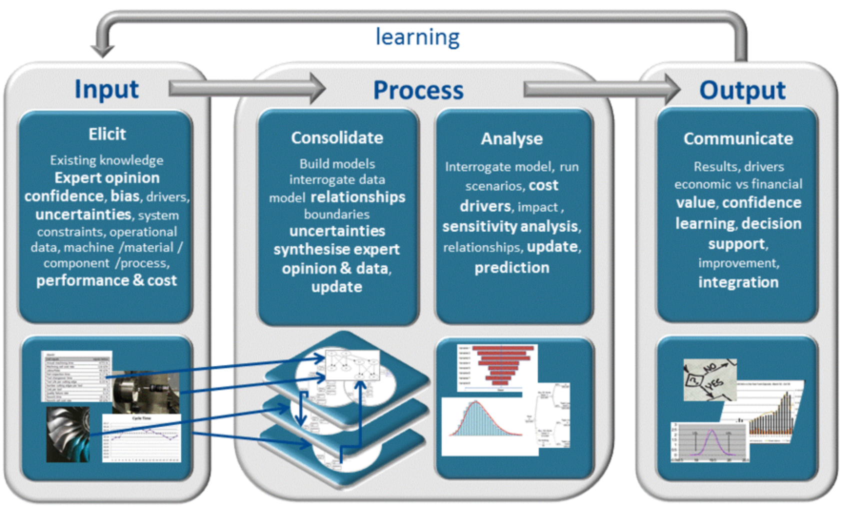

Figure 3. Conceptual framework for value-focussed decision making within advanced manufacturing R&D.

For the framework to be successful each of these aspects needs to be addressed. In particular the highlighted areas require further detailed investigation as there are currently no standardised solutions for use in this particular environment.

3.3. Capturing the requirements

The data requirements for populating the framework will depend on the system being modelled and the costing methodology chosen to represent the system. Qualitative and quantitative cost and performance data is required from existing R&D to populate the framework. Utility information is essential for metrics which will determine cost and quality decision boundaries [27]. A qualitative scale can be used to account for technology readiness, environmental impact, health and safety implications, and confidence and risk [28]. Capturing real time information relevant to the whole system will encourage information sharing and provides an environment for creating new knowledge [19].

3.4. Eliciting information

Information can be taken from existing databases or collected via interviews. Qualitative research literature gives insight into the most appropriate theories and methods to elicit and analyse the expert knowledge [29]. Semi-structured interviews provide a reliable method in this type of application [30].

The recommended process for the elicitation of expert opinion is shown in Table 3. The consensus among practitioners is that providing feedback can help to alleviate many issues with opinion bias from a group of experts, offering the 'opinion givers' an opportunity to revise their original estimate [31]–[33].

Table 3. Considerations for the elicitation of expert opinion (adapted from Kuhnert et al [34]).

Issues	Interpretation	Possible solution
Overconfidence	Overestimating accuracy of beliefs, underestimating uncertainty in a process.	Incorporating feedback mechanism
Conseratism	An expert understating their belief	
Representativeness	Opinions based on similar situations	
Availability	Basing a response on current information not on past events	Considerations of resoiurces. Availability of experts.
Anchoring and adjustment	Groups anchoring around initial estimates	Elicit the uncertainty around responses. For multiple experts, synthesise their responses.
Misunderstanding of conditional probabilities	Confusion of definition of conditional probabilities	Design around the available expert(s) Information from experts can be translated into prior probabilities.
Translation	Confusion in the translation of a response to alternative scale	
Affect	Experts emotions	Examine the impact of priors. Where empirical data are available, run the models with and without the influence of informative priors.
Hindsight bias	Expert placing too much emphasis on past events	
Law of small numbers	Experts generalising their opinion	
Linguistic uncertainty	Misunderstanding the question	Clearly articulate the research question

3.5. Handling uncertainty

Uncertainty is complex and not necessarily resulting from a lack of knowledge – uncertainty can occur in situations with a lot of available information. Moreover the emergence of new information can both reduce and increase the level of uncertainty [35]. Uncertainty can be characterised according to a number of dimensions [36]:

1. Reliability (precision, credibility, uncertainty of the information quality)
2. Completeness (gaps, inconsistent definitions)
3. Accessibility (availability, rights of access, communication, format)
4. Relevance (usefulness in terms of decision making)
5. Representativeness (internal and external boundary issues, quantification)
6. Repeatability (variation in learning curves, consistency and reproducibility in data collection methods).

Uncertainty in research and development environments is the major source of risk and opportunity and causes many complications when developing a robust decision system, so a way to manage this uncertainty is critical [7], [13], [37]. A number of approaches for handling uncertainties in manufacturing knowledge exist, including simulation based approaches, Bayesian Networks (BN), Artificial Neural Networks (ANN), and Fuzzy systems. BN are provisionally favoured for the framework due to ease of use, mathematical rigour and suitability for system integration.

4. Conclusion

The need for a systematic value-driven decision framework for use in manufacturing research environments has been identified. A solution such as this does not currently exist, almost certainly due to the complexity of modelling the information within this type of environment.

This paper has argued that a synthesis of research methods is required. The framework is being developed through mixed methods research with a synthesis of modelling techniques. The framework draws on and extends existing research in the appreciation and challenges of the introduction of cost into early phases of development, the areas of knowledge and uncertainty management with in the context of applied manufacturing R&D, decision making through early phases of technology development. The framework is being operationalised with the decision makers and stakeholders to ensure that the scope and flexibility is anticipated and incorporated throughout its development. This research has the potential to be extended to other centres of a similar nature.

4.1. Limitations

A limitation of this work is that successful implementation of the framework demands that these research environments establish a standardised process for knowledge management. Whilst BN have been provisionally selected for uncertainty management, this decision has not been based on a comprehensive evaluation of all alternative methods could be performed; such testing is out of scope of the research aims.

4.2. Recommendations for further work

The next phase of this research is to operationalise and generalise the framework using two case studies. The first supports the introduction and roll out of a novel technology into an established process. The second is the advancement of the framework to select the most cost effective technologies from across the MCRL scale.

Mixed methods have been used to develop the research into a conceptual framework. The cycles of action research combined with the rigour of the Lean Six-Sigma [38] approach will enable the operationalisation of the framework through cycles of collaborative planning, acting, evaluating and developing to maximise the success of a value-focussed decision framework.

The chosen framework architecture is an object tree incorporating a cost versus capability (value) model, providing a hierarchical representation of the relationship between cost functions within a process. The synthesis of quantitative and qualitative knowledge as well as uncertainty modelling will be provided by Bayesian networks. Value functions will be employed for visualisation of trade-off alternatives.

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References

[1] M. Johnson and R. Kirchain, Quantifying the effects of parts consolidation and development costs on material selection decisions: A process-based costing approach, *Int. J. Prod. Econ.*, Vol. 119, No. 1, 2009, pp. 174–186.

[2] G. S. Ford, D. Ph, et al., A valley of death in the innovation sequence:an economic investigation, *phoenix Cent. Adv. Leg. Econ. Public. policy Stud.*, 2007.

[3] R. Roy and C. Kerr, Cost Engineering: Why, What and How?, *Decis. Eng. Rep. Ser.*, 2003, pp. 2–5.

[4] R. Curran, S. Raghunathan, et al., Review of aerospace engineering cost modelling: The genetic causal approach, *Prog. Aerosp. Sci.*, Vol. 40, No. 8, 2004, pp. 487–534.

[5] U. Ibusuki and P. C. Kaminski, Product development process with focus on value engineering and target-costing: A case study in an automotive company, *Int. J. Prod. Econ.*, Vol. 105, No. 2, 2007, pp. 459–474.

[6] S. Morgan, P. Grootendorst, et al., The cost of drug development: A systematic review, *Health Policy,* New York, Vol. 100, No. 1, 2011, pp. 4–17.

[7] Y. Xu, F. Elgh, et al., Cost Engineering for manufacturing: Current and future research*, Int. J. Comput. Integr. Manuf.*, Vol. 25, No. 4–5, 2012, pp. 300–314.

[8] D. Ben-Arieh and L. Qian, Activity-based cost management for design and development stage, *Int. J. Prod. Econ.*, Vol. 83, No. 2, 2003, pp. 169–183.

[9] J. Scanlan, T. Hill, et al., Cost modelling for aircraft design optimization, *J. Eng. Des.*, Vol. 13, No. 3, 2002, pp. 261–269.

[10] F. Elgh and M. Cederfeldt, Concurrent cost estimation as a tool for enhanced producibility-System development and applicability for producibility studies, *Int. J. Prod. Econ*., Vol. 109, No. 1–2, 2007, pp. 12–26,.

[11] L. Qian and D. Ben-Arieh, Parametric cost estimation based on activity-based costing: A case study for design and development of rotational parts, *Int. J. Prod. Econ.*, Vol. 113, No. 2, 2008, pp. 805–818.

[12] E. Shehab and H. Abdalla, Manufacturing cost modelling for concurrent product development, *Robot. Comput. Integr. Manuf.*, Vol. 17, No. 4, 2001, pp. 341–353.

[13] J. A. Erkoyuncu, R. Roy, et al., Understanding service uncertainties in industrial product–service system cost estimation, *Int. J. Adv. Manuf. Technol.*, Vol. 52, No. 9–12, 2011, pp. 1223–1238.
[14] K. Agyapong-Kodua, R. Brown, et al., An integrated product–process design methodology for cost-effective product realisation, *Int. J. Comput. Integr. Manuf.*, Vol. 25, No. 9, 2012, pp. 814–828.
[15] N. Chungoora, G. a. Gunendran, et al., *Extending product lifecycle management for manufacturing knowledge sharing*, Proc. Inst. Mech. Eng. Part B J. Eng. Manuf., 2012.
[16] M.-C. Nadeau, A. Kar, et al., A dynamic process-based cost modeling approach to understand learning effects in manufacturing, *Int. J. Prod. Econ.*, Vol. 128, No. 1, 2010, pp. 223–234,.
[17] R. Roy, S. Colmer, et al., Estimating the cost of a new technology intensive automotive product : A case study approach, *Int. J. Prod. Econ.*, Vol. 97, No. 2, 2005, pp. 210–226.
[18] S. Polasky, S. R. Carpenter, et al., Decision-making under great uncertainty: Environmental management in an era of global change, *Trends Ecol. Evol.*, Vol. 26, No. 8, 2011, pp. 398–404.
[19] B. Rubenstein-Montano, J. Liebowitza, et al., A systems thinking framework for knowledge management, *Decis. Support Syst.*, Vol. 31, No. 1, 2001, pp. 5–16.
[20] T. Gavrilova and T. Andreeva, Knowledge elicitation techniques in a knowledge management context, *J. Knowl. Manag.*, Vol. 16, 2012, pp. 523–537.
[21] H. Arksey and P. T. Knight, *Interviewing for social scientists: an introductory resource with examples.* SAGE, 1999.
[22] B. G. Kingsman and A. De Souza, A knowledge-based decision support system for cost estimation and pricing decisions in versatile manufacturing companies, *Int. J. Prod. Econ.*, Vol. 53, 1997, pp. 119–139.
[23] M. J. Ward, S. T. Halliday, et al., A readiness level approach to manufacturing technology development in the aerospace sector: an industrial approach, *Proc. Inst. Mech. Eng. Part B J. Eng. Manuf.*, Vol. 226, No. 3, 2011, pp. 547–552.
[24] J. Simmons and I. Lovegrove, Bridging the conceptual divide: lessons from stakeholder analysis, *J. Organ. Chang. Manag.*, Vol. 18, No. 5, 2005, pp. 495–513.
[25] R. B. Johnson and A. J. Onwuegbuzie, *Mixed methods research: A research paradigm whose time has come*, 1990.
[26] R. B. Johnson, A. J. Onwuegbuzie, et al., Toward a definition of mixed methods research, *J. Mix. Methods Res.*, Vol. 82, No. 3, 2007, pp. 274–275.
[27] S. M. Paul, D. S. Mytelka, et al., How to improve R&D productivity: the pharmaceutical industry's grand challenge, *Nat. Rev. Drug Discov.*, Vol. 9, No. 3, 2010, pp. 203–14.
[28] I. N. Chengalur-Smith, D. P. Ballou, et al., The impact of data quality information on decision making: an exploratory analysis, *IEEE Trans. Knowl. Data Eng.*, Vol. 11, No. 6, 1999, pp. 853–864.
[29] M. Saunders, P. Lewis, et al., *Research methods for business students*, 6th ed. Pearson Education Limited, 2012.
[30] H. Arksey and P. T. Knight, Achieving a successful interview, In: *Interviewing for Social Scientists*, H. Arksey and P. T. Knight, Eds. London: SAGE Publications Ltd, 1999, pp. 89–109.
[31] T. G. Martin, M. A. Burgman, et al., Eliciting expert knowledge in conservation science, *Conserv. Biol.*, Vol. 26, No. 1, 2012, pp. 29–38.
[32] G. Tichy, The over-optimism among experts in assessment and foresight, *Technol. Forecast. Soc. Change*, Vol. 71, No. 4, 2004, pp. 341–363,.
[33] F. Brandes, The UK technology foresight programme: An assessment of expert estimates, *Technol. Forecast. Soc. Change*, Vol. 76, No. 7, 2009, pp. 869–879.
[34] P. M. Kuhnert, T. G. Martin, et al., A guide to eliciting and using expert knowledge in Bayesian ecological models, *Ecol. Lett.*, Vol. 13, 2010, pp. 900–914.
[35] O. Perminova, M. Gustafsson, et al., Defining uncertainty in projects - a new perspective, *Int. J. Proj. Manag.*, Vol. 26, No. 1, 2008, pp. 73–79.
[36] C. Durugbo, J. A. Erkoyuncu, et al., Data uncertainty assessment and information flow analysis for product-service systems in a library case study, *Int. J. Serv. Oper. Informatics*, Vol. 5, No. 4, 2010.
[37] T. Masood, J. A. Erkoyuncu, et al., Integrating design attributes, knowledge and uncertainty in aerospace sector, *CIRP J. Manuf. Sci. Technol.*, Vol. 7, No. 2, 2014, pp. 83–96.
[38] M. P. J. Pepper and T. a. Spedding, The evolution of lean Six Sigma, *Int. J. Qual. Reliab. Manag.*, Vol. 27, No. 2, 2010, pp. 138–155.