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Knowledge management and knowledge discovery for process improvement and sustainable manufacturing: a foundry case study

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Abstract Defect reduction is an essential step for the implementation of process improvement and sustainable manufacturing strategies. In the foundry industry minimisation of defects poses immense challenges due to the complexity of production processes with hundreds of factors influencing the quality of the final casting as well as part specific quality constraints. Process improvement methodologies like Six Sigma and Lean Manufacturing have traditionally been applied to address these challenges but, in order to develop smart and sustainable growth strategies, there is the need to retain and re-use the intellectual property that is created during these activities. This paper discusses the role that knowledge management plays in assisting process engineers to discover improvement opportunities. It also proposes a new methodology, called 7Epsilon, that links product specific process knowledge and current data analysis practices to achieve zero defect manufacturing. As part of the 7Epsilon methodology (http://www.7epsilon.org) a novel data driven approach to discover noise free correlations among process factors and responses is illustrated through a practical case study.

1. Introduction

Despite many advances in manufacturing technologies the cost of quality is still considerable in terms of lost revenues and environmental impact. In 2010, it was estimated that 1% rejection rate in the foundry industry would lead to a loss of $1.3 billion and produce an environmental impact quantified as 0.46 M tonnes of landfill waste and CO2 emission equivalent to 920,000 green cars [1]. In recent years a variety of approaches have been developed to achieve compliance to customer requirements and legislation through continuous process improvement, defect reduction and waste minimization. ISO9001 is the main set of standards and it is designed to help organizations ensure that they meet the needs of customers. Other initiatives like Six Sigma, Total Quality Management and Lean Manufacturing provide instead some practical tools and methodologies to enable an organisation to improve on a continuous basis not only by enhancing customer satisfaction, but also by gaining efficiencies such as reducing the cost of rework, decrease cycle time and improve productivity. While some methodologies like Six Sigma heavily rely on data collection and statistical techniques, others such as Lean Manufacturing focus on improving processes by minimising waste and reducing non-value activities. Total Quality Management is instead a structured approach to quality improvement which involves ongoing refinements in response to continuous feedback. Although these approaches are quite diverse they have been applied to a number of industries with different degrees of success. When properly implemented they have proved to be suitable for achieving higher level of efficiencies with respect to specific customer needs but some authors warn that they may fail to sustain competitive advantage and innovation [2]. No matter what is the approach chosen, it is well acknowledged that continuous process improvement activities can only be successful with strong commitment of managers and individual team members, who are willing to share their expertise and knowledge for fulfilling specific business objectives. In the context of Six Sigma projects knowledge-creation practices, especially those that capture team-members knowledge, are key factors that contribute to the success of process improvement projects [3].

Data driven methodologies such as Statistical Process Control or DOE (Design of Experiments) are also very useful to find improvement opportunities by limiting variations within the process and detecting states when the process is out of control. However, the implementation of these techniques may become unpractical and fail for complex industrial processes. In the case of foundries, it is not enough to control process variables in a generic way [4]. This is due to several reasons. First of all, in a typical foundry, process outputs are the results of complex interactions among many input variables (at least 20-40 process variables). Secondly, variable thresholds do not only depend on the process itself but they are also related to the product characteristics [4]. In a recent publication product specific process knowledge has been defined as "the actionable information that can be revealed by analysing patterns of in-process data and discovering optimal ranges of input factors to achieve a specific business goal "[1]. In mathematical terms the complexity of casting process optimisation is due to the fact that each foundry has its own product specific local optimum. Each local minimum (or maximum) can be achieved by performing small adjustments and improvements to the foundry own "recipe", ultimately leading to significant savings in terms of cost reduction and waste minimisation. Available literature can often help process engineers in achieving process improvement objectives, but in most cases both variables relationships and optimal conditions are process specific. Alternatively and to complement findings from published research process engineers can try to discover process characteristics from data. In a foundry situation a process engineer needs to be able to identify, in a set of noisy in-process data, a small number of root causes from weak correlation patterns. Furthermore in order to infer causal relationships existing product specific process knowledge needs to be made readily available to support decision making.

In this paper we discuss the role that knowledge management practices play to support continual process improvement and sustainable manufacturing strategies. Furthermore an innovative methodology, called 7Epsilon (7ε), is proposed. The latter is a systematic approach for using existing in-process data and discovering, retaining and reusing product specific process knowledge in order to stimulate a culture of innovation within the organisation. The 7ε initiative is led by Dr. Rajesh Ransing at Swansea University along with a consortium of European universities and research organisations. Although its main application is casting process optimisation, its principles can be generalised to other industries. The paper is structured as follows. Section 2 focuses on the theoretical foundations of knowledge management in industry and discusses how knowledge management can facilitate process improvement activities. The 7ε methodology applied to the foundry industry is described and discussed in Section 3 and the paper is concluded in Section 4.

2. Knowledge management in industry

Knowledge management is a relatively young discipline and concerns with the practice of creating, capturing, retrieving, and applying organisational knowledge in order to achieve strategic aims such as improved performance, cost reduction or fulfilment of legal or social constraints [5]. Nonaka and Takeuchi suggest that the success of companies depends on the ability to consistently create new knowledge, disseminate it widely throughout the organization, and quickly embody it in new technologies and products [6]. Davenport and Prusak ([7] p. ix) define Knowledge Management as: "to identify, manage, and value items that the organization knows or could know: skills and experience of people, archives, documents, relations with clients, suppliers and other persons and materials often contained in electronic databases". From this definition it clearly emerges that the management of organisational knowledge is a complex task which involves continuous interaction between technologies, people and processes as well as managing different types of knowledge generated by an organisation, including intangible knowledge like know-how and people skills and explicit knowledge communicated and articulated through spoken and written words as well as knowledge stored in databases. Although the management of knowledge does not necessary implies the use of IT, undoubtedly IT systems have enabled and facilitated the creation of knowledge management systems for the effective management of enterprise knowledge. Examples of knowledge management systems in an organisation include wikis, document management systems, on line directories, lesson learnt or best practice libraries, expert and decision making systems, just to mention a few. Nowadays, due to growing popularity of internet based technologies for sharing content and data, IT tools are widely recognised as major facilitators for the implementation of knowledge management strategies. Despite this a major issue, also known as the “Babel-tower effect", arises from interoperability problems due heterogeneity and multi-view perspective of information hold by the organisation [8]. In order to achieve a comprehensive knowledge management strategy there is the need to develop frameworks that enable sharing of data and information among different departments as well as among different enterprises. Another limitation derives from the so called “information overloading" issue. IT systems have grown so rapidly that nowadays companies hold terabytes of data and knowledge retrieval has become a cumbersome task for the end user. There is an immediate need for more effective knowledge retrieval functionalities and search engines to support decision making.

As discussed in [9] important practical aspects to take into consideration when implementing a knowledge management system are: a) the creation of new knowledge, b) knowledge storage and retrieval, c) knowledge transfer and d) knowledge application. Knowledge creation and storage are interrelated. In fact, organisational knowledge can only be stored once it has been created or made explicit. On the other hand the availability of IT based knowledge storage systems can also enhance the capability of a company of creating new knowledge.

2.1 Knowledge Creation

Different mechanisms that lead to the creation of knowledge have been described by Nonaka and Takeuchi [6] and represented in a knowledge creation spiral as depicted in Figure 1.

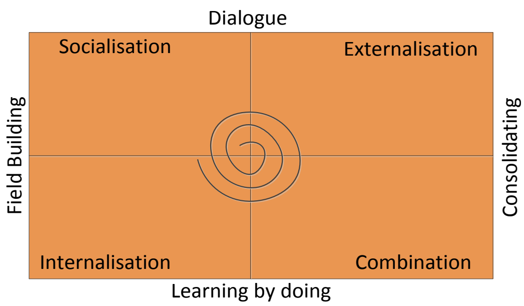

Figure 1 - The Knowledge Creation Spiral [6] includes different mechanism for knowledge creation: externalisation, combination, internalisation and socialisation.

First of all knowledge can be created by externalisation which is the process of transforming tacit knowledge into explicitly knowledge. Externalisation is an essential step for the creation of new organisational knowledge which can be achieved through the personal commitment of individuals. An alternative way of creating knowledge is to combine existing explicit knowledge, also known as combination [6]. Humans are often good at interpreting and combining existing pieces of information to create new knowledge. However, within an enterprise this ability is often hindered by the fact that too much information is available which is too complex to be analysed and being processed by the human brain. In this case the use of statistical and machine learning techniques can help to create new knowledge by combining existing explicit knowledge. During process improvement activities new knowledge is continually created either by externalisation and/or combination. Example of activities involving externalisation processes are brainstorming meetings where knowledge about certain process characteristics are discussed among team members considering different viewpoints. The outcome of these meetings is usually the codification of tacit knowledge into pictorial or written forms [10, 11]**.** For instance, process engineers may draw cause effect diagrams, process maps, factor lists to better understand the process itself and what affects the quality of the output. The importance of externalisation in process improvement activities should not be underestimated because, as suggested in [12], tacit knowledge is a source of success and plays a crucial role in fostering innovation. Hence, when implementing data driven methodologies for process improvement, companies should try to avoid focusing only on knowledge creation by combination [13].

Another important aspect of knowledge creation is socialisation. In process improvement, knowledge creation through socialisation is achieved by forming cross functional teams [3]. The advantage of socialisation is that knowledge transfer happens without the need of codifying the knowledge in an explicit form, but it might be time consuming and communication needs to be encouraged and facilitated. Communication barriers may arise from the lack of a common vocabulary and shared understanding. Finally internalisation, which also requires individual commitment, is another aspect of knowledge creation. Internalisation occurs when the explicit knowledge is again transformed into tacit knowledge of individuals. The availability of knowledge management systems to store knowledge acquired during previous process improvement initiatives can contribute to internalisation of knowledge and enable knowledge transfer within an organisation.

2.2 Knowledge Storage and Retrieval

The ability to efficiently store and retrieve organisational knowledge is one of the key aspects of knowledge management. The choice of appropriate storage and retrieval methods highly depends on the kind of knowledge that needs to be stored. A relational database can be useful to store some kind of declarative knowledge, while Artificial Intelligence techniques are employed to store relational or causal knowledge. Since the ultimate aim of knowledge management is the use of knowledge to fulfil specific business objectives, knowledge storage should focus on a selected body of knowledge [7]. Also knowledge should be codified in a way that it retains its meaning and purpose. For instance, once procedural knowledge is recorded in a database system the meaning is lost as it becomes raw data [7]. Ontology based approaches, which will be described more in detail in Section 2.4, try to address this problem by providing alternative knowledge codification methods where the meaning is retained. In order to effectively re-use knowledge appropriate retrieval methods must exist. For the purpose of knowledge retrieval a distinction can be made between structured and unstructured knowledge. This classification concerns with the formats in which knowledge can be stored. Relational databases or tagged documents can be thought as formats to codify and store structured knowledge while e-mails and informal conversation forums can be classified as unstructured knowledge. When knowledge has a structure is more easily retrieved and retained but the process of organising knowledge is time consuming and it requires specialised resources. Unstructured knowledge instead is highly dynamic and grows fast but it is harder to be retrieved at a later stage.

2.3 Knowledge Transfer/Application

Knowledge transfer is an essential process to ensure knowledge is effectively shared for the benefit of an organisation. Alongside with knowledge application, knowledge transfer is one of the major driving forces for the development of knowledge management strategies. Knowledge transfer is a broad term and includes mechanisms to move knowledge between two individuals, between an individual and an explicit source, an individual and a group or among groups of individuals [9]. A number of initiatives can support knowledge transfer at different levels involving different transfer channels as depicted in Figure 2. Knowledge application refers to the use of knowledge assets for the fulfilment of a specific aim or action. Appropriate application of enterprise knowledge can enhance decision making capabilities, increase efficiency and lead to innovation.

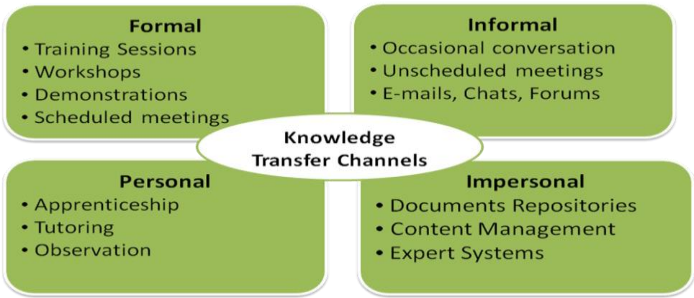

Figure 2 – Categorisation of Knowledge Transfer Channels by Holtham and Courtney [14].

Alavi et al. [9] state that the source of competitive advantage is the application of knowledge rather than the knowledge itself. Knowledge application mechanisms include organisational directives and routines (such as procedures, standards and interaction protocols) aimed at increasing efficiency in day to day business operations as well as task oriented activities where individuals gather together to solve particular problems [15]. In order to facilitate knowledge transfer and application it is important that, during process improvement activities, an emphasis is given to all knowledge creating activities as well as re-using existing knowledge. Documentation overload can be an obstacle to achieve effective knowledge application. In fact although knowledge can be stored in a persistent storage medium it might become too large and difficult to access timely and appropriately to support decision making. Ontology based approaches, which are described in the next session, address this limitation.

2.4 Ontology Based Approaches for Knowledge Management

Ontology based approaches for the management of enterprise knowledge have gained a great deal of attention in recent years. In industry ontologies are used to solve conflicts due to the heterogeneity of information among different business and operational layers of an enterprise or a network of enterprises, the so called “Babel-tower effect”. In a scenario of an extended enterprise comprising of several interconnected partners, an ontology can be used to agree on a well defined terminology of the domain of interest [16]. The term ontology is quite broad and ontologies may be developed with different degrees of formalisation using different languages. They can range from being just taxonomical definition of terms (lightweight ontologies) to being complex representations of some domain knowledge including rules and axioms and hence providing the capability to generate logical inference (heavyweight ontologies). In manufacturing information systems, ontologies find a widespread application to integrate multi-source and heterogeneous data, information and domain knowledge [17]. Several authors have demonstrated how the use of ontology can support knowledge representation to facilitate FMEA [17-19]. The Semantic Web initiative uses ontologies as a backbone to provide explicit semantics that allow data sharing and reuse across web application (http://www.semanticweb.org). The idea of the Semantic Web is that by developing semantically linked data it will be possible to perform searches that are related to the meaning of a particular text rather than a mere sequence of characters, hence improving recall and precision and reducing the time required to find information.

3 The 7 Epsilon Methodology: a foundry case study

As stated by Clause 8 of the ISO9001:2008 standard, industries are required to analyse in-process data to discover process improvement opportunities and develop corrective and preventive action plans. In the manufacturing industry, improvement opportunities are also part of the implementation of wider sustainable manufacturing strategies aimed at reducing waste and promoting a better use of resources. The 7 Epsilon (7ε) framework [20], , illustrated in Figure 3, is new way of using existing in-process data and discovering, retaining and reusing product specific process knowledge in order to stimulate a culture of innovation within the organisation. 7ε integrates data driven and knowledge management approaches for zero defect manufacturing, improves traceability and builds inspiring teams of engineers by accumulating and reusing foundry and product specific process knowledge. According to the 7ε methodology an important pre-requisite for achieving zero defect manufacturing is the ability of re-using existing process knowledge. In order to achieve this goal a prototype system for storage and retrieval of foundry process knowledge has been developed to include a wide variety of digital contents from different sources as illustrated in Figure 3.

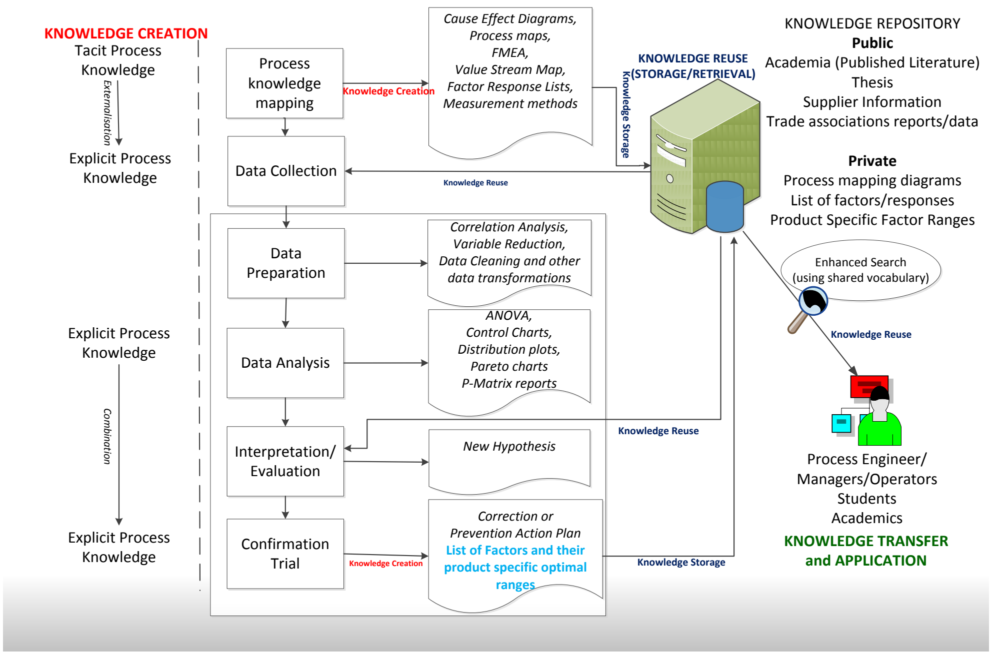

Figure 3 - 7ε improves traditional approaches to zero defect manufacturing by focusing on innovation through knowledge sharing and reuse [20].

3.1 Foundry Process Knowledge repository for knowledge reuse

The main purpose of the 7ε knowledge repository is to assist process engineers and practitioners to formulate new hypothesis by linking data driven methodologies with process knowledge acquired by academia or through previous process improvement activities. The knowledge creation loop is then completed by developing confirmation trials to test the new hypothesis which, if confirmed, will become part of the knowledge base. The prototype is build by using DSpace (http://www.dspace.org/), an open source and customisable digital repository software widely adopted by academia and many organisations. DSpace can store and organise a wide range of digital contents, including pictures, documents and data files. It embeds advanced search capabilities to include full text and metadata based search. This means respectively that the user can search specific terms either in the corpus of the document or in special fields, called “metadata” (e.g. author, title, subject, abstract etc.). Furthermore in order to overcome problems due to ambiguity of terms or incorrect use of metadata, standard DSpace search capabilities have been enhanced by using the Controlled Vocabulary adds-on that allows specifying metadata from a fixed taxonomy [21].

In ontological engineering, taxonomies are considered lightweight ontologies. When used in the context of document retrieval they allow to standardise document descriptions and to simplify subsequent searches by establishing a common language in a given domain [21].The foundry taxonomy that drives the 7ε knowledge repository has been developed in XML (Extensible Markup Language). Its main purpose is to structure and organise process knowledge stored in digital artefacts with the final aim to overcome document overload issues and improve search precision. Furthermore the taxonomy can also be used to develop and promote a common understanding of process improvement terminology that can be useful during brainstorming meetings. The choice of a lightweight ontology for building the 7ε knowledge repository is justified by the fact that although taxonomies do not have full expressive power they offer a good trade off between enhanced retrieval and easiness of implementation and maintenance. Future research will address the impact of adopting more complex ontologies as backbone of the 7ε repository.

3.2 Process Knowledge Discovery in Steel Casting

As part of the 7ε framework, research has been undertaken to address some of the shortcomings of traditional data driven approaches to discover product specific process knowledge in the foundry industry. Commercial and technical challenges that the industry is facing are highlighted in [1]. Furthermore a new methodology using the concept of co-linearity index to quantify noise free correlations was also presented in [1]. The main purpose of the co-linearity index is to help process engineers in root cause analysis. Previous work on using Bayesian Network [22] or Neural Network [23] for analysing in-process data had limited response from the foundry industry. In order for the prior knowledge to be learnt robustly, new hypothesis or opportunities need to be generated by analysing sometimes weak patterns in a set of noisy in-process data. The co-linearity index can guide process engineer in finding these weak patterns and is calculated by using Principal Component Analysis, a dimensionality reduction technique that removes noise and highlights the most important factors that affect a process response. The application of the co-linearity index methodology technique allows visualising process variables via co-linearity plots. Recently the methodology has been extended to categorical variables in addition to continuous ones [24]. An example of co-linearity plot that has been developed of part of process improvement activities of a stable steel casting process is depicted in Figure 4. The co-linearity plot shows the pair wise correlation between several process factors and Charpy V-notch test (CVN at 70) response. Prior to performing co-linearity index calculation several data pre-processing techniques are applied to factors to be able to juxtapose categorical and continuous data in a global table and to take into account the effect of outliers. Furthermore responses are scaled using a penalty matrix approach which gives low values of penalty to desirable responses and high values to undesirable responses [1].

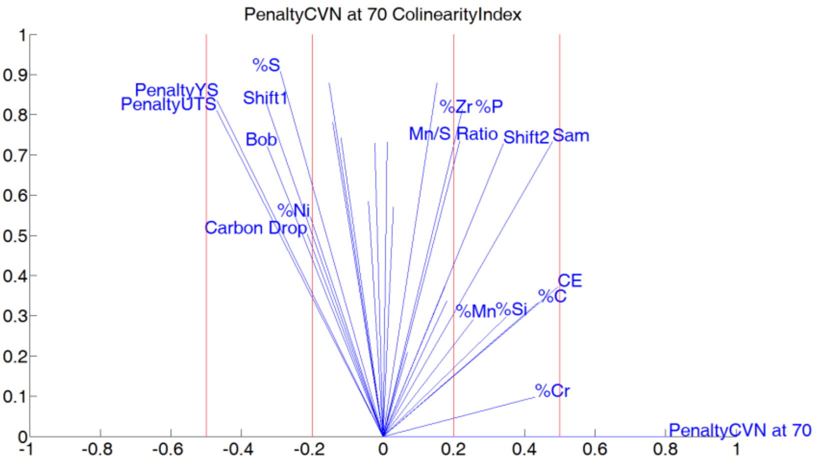

Figure 4 - The co-linearity index plot for a stable steel casting process. The factors that have more importance in determining the process outputs are highlighted. Categorical variables such as operator *Sam* and *Shift 2* show a certain degree of positive correlation with penalty values of CVN at 70 which will need further investigation.

The full set of data transformation and the co-linearity index algorithm are described in [24]. The co-linearity plot has been used in process improvement meetings to guide process engineers in discovering root causes that affect the quality of the final casting.

4. Conclusions

In this paper a new framework to achieve zero defect manufacturing in the foundry industry is discussed. The 7ε overcomes limitations of current process improvement approaches by adding a layer of innovation through knowledge discovery and re-use. A knowledge repository prototype system is proposed to create, retain and re-use foundry product specific process knowledge. The knowledge repository combined with the co-linearity index approach, also described in this paper, can assist process engineers to formulate new hypothesis about possible root causes of defects.

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5. References

[1] Ransing, R. S., Giannetti, C., Ransing, M. R., and James, M. W., A coupled penalty matrix approach and principal component based co-linearity index technique to discover product specific foundry process knowledge from in-process data in order to reduce defects., Computers in Industry. Vol. 64:5, pp. 514-523, (2013).

[2] Parast, M. M., The effect of Six Sigma projects on innovation and firm performance, International Journal of Project Management. Vol. 29:1, pp. 45-55, (2011).

[3] Anand, G., Ward, P. T., and Tatikonda, M. V., Role of explicit and tacit knowledge in Six Sigma projects: An empirical examination of differential project success, Journal of Operations Management. Vol. 28:pp. 303-315, (2019).

[4] Roshan, H. M., Start gaining process knowledge, Modern Casting May 2013, American Foundry Society,. (2013).

[5] Lehaney, B., Clarke, S., Coales, E., and Gillian, E., *Beyond Knowledge Management*: London: Idea Group Publishing, 2004.

[6] Nonaka, I. and Takeuchi, H., *The Knowledge-Creating Company*: New York: Oxford University Press, 1995.

[7] Davenport, T. H. and Prusak, L., *Working knowledge: how organizations manage what they know*: Harvard Business School Press, 2000.

[8] Panetto, H., Dassisti, M., and Tursi, A., ONTO-PDM: Product-driven ONTOlogy for Product Data Management interoperability within manufacturing process environment, Advanced Engineering Informatics. Vol. 26:2, pp. 334-348, (2012).

[9] Alavi, M. and Leidner, D. E., Review: Knowledge management and knowledge management systems: Conceptual foundations and research issues., MIS Quarterly. Vol. 25:1, pp. 107-136, (2001).

[10] Bohn, R. E., Measuring and managing technological knowledge. , Sloan Management Review. Vol. 36:1, pp. 61-73, (1994).
[11] Hansen, M. T., Nohria, N., and Tierney, T., What's your strategy for managing knowledge?, Harvard Business Review. Vol. 77:2, pp. 106-116, (1999).
[12] Alwis, R. S. and Hartmann, E., The use of tacit knowledge within innovative companies: knowledge management in innovative enterprises, Journal of Knowledge Management. Vol. 12:1, pp. 133-147, (2008).
[13] Wu, C. and Lin, C., Case study of knowledge creation facilitated by Six Sigma, Journal of Quality & Reliability Management. Vol. 26:9, pp. 911-932, (2009).
[14] Holtham, C. and Courtney, N., The executive learning ladder: A knowledge creation process grounded in the strategic information systems domain, AMCIS 1998 Proceedings. (1998).
[15] Grant, R., Toward a knowledge-based theory of the firm, Strategic Management Journal. Vol. 17:Winter Special Issue, pp. 109-122, (1996).
[16] Choudhary, A. K., Harding, J. A., and Khilwani, N., Semantic web in manufacturing, Proceedings of the Institution of Mechanical Engineers Part B: Journal of Engineering Manufacture. Vol. 223:7, pp. 905-924, (2009).
[17] Zhao, X. and Zhu, Y., Research of fmea knowledge sharing method based on ontology and the application in manufacturing process, Database Technology and Applications (DBTA), 2010 2nd International Workshop. pp. 1-4, (2010).
[18] Ebrahimipour, V., Rezaie, K., and Shokravi, S., An ontology approach to support fmea studies., Expert Systems with Applications. Vol. 37:1, pp. 671-677, (2010).
[19] Mikos, W. L., Ferreira, J. C. E., Botura, P. E. A., and Freitas, L. S., A system for distributed sharing and reuse of design and manufacturing knowledge in the PFMEA domain using a description logics-based ontology, Journal of Manufacturing Systems. Vol. 30:3, pp. 133-143, (2011).
[20] Roshan, H. M., Giannetti, C., Ransing, M. R., Ransing, R. S. "If only my foundry knew what it knows …": A 7Epsilon perspective on root cause analysis and corrective action plans for ISO9001:2008, World Foundry Conference, Bilbao, Spain May 2014 (under review) (2014).
[21] Ferreira, M. and Baptista, A., The use of taxonomies as a way to achieve interoperability and improved resource discovery in DSpace-based repositories, 2005.
[22] Lewis, R. W. and Ransing, R. S., A semantically constrained Bayesian network for manufacturing diagnosis, International Journal of Production Research. Vol. 35:8, pp. 2171-2178, (1997).
[23] Ransing, R. S. and Lewis, R. W., A semantically constrained neural network for manufacturing diagnosis, International Journal of Production Research. Vol. 35:9, pp. 2639-2660, (1997).
[24] Giannetti, C., Ransing, R. S., Ransing, M. R., Bould, D. C., *et al.*, A novel variable selection approach based on co-linearity index to discover optimal process settings by analysing mixed data, Computes & Industrial Engineering (under review).