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A simulation approach to innovation deployment readiness assessment in manufacturing

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ABSTRACT

Manufacturing companies need to continuously innovate in order to remain competitive. Fostering a successful innovative environment should reflect positively on manufacturing performance, with a premise that companies seek to attain appropriate level of readiness when deploying their innovation. This paper presents an approach to assessing innovation deployment readiness in manufacturing. Deployment is conceptualised as a sequential decision process that involves a deployment plan to be executed sequentially in an uncertain environment. The deployment plan is assessed using simulation to account for risks and uncertainties that may characterise the deployment activities in the target environment and the capabilities put forward in the plan for handling the risks and uncertainties. The approach is illustrated using a simulated manufacturing job shop scenario and the results show that deployment readiness can vary over time. Deployment readiness can be improved by identifying the states in which readiness is weak and taking appropriate actions.

1. Introduction

Intensive competition in global markets has made innovation a condition for survival of companies. As a consequence, there is increasing pressure on companies to continuously innovate and maintain appropriate strategy. Continuous innovation is an ongoing process and its primary purpose is to gain better performance whilst maintaining competitiveness (Davison & Hyland, 2006; Steiber & Alänge, 2013). To be competitive, manufacturing companies need to continuously innovate. That is, ensure ongoing interaction between operations and incremental improvement aimed at effectively combining operational effectiveness, strategic flexibility and learning. Manufacturing companies that engage in ongoing upgrades or enhancements of existing technologies, processes or products are continuously innovative. Such companies will have the ability to change their business or management model as well as to develop, or adopt, and implement new products, processes and technologies that respond to customer needs. Successful engagement in continuously innovative environments should reflect positively on manufacturing performance (Kastalli & Van Looy,

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2013) and this is premised on the companies attaining the appropriate level of readiness to deploy their innovation initiatives.

Deployment of innovation initiatives in manufacturing can take several forms and deployment success depends on degree of readiness. Innovation initiatives in the context of manufacturing operations and processes, which is of interest in this paper, include for example Statistical Process Control (SPC) (Lim & Antony, 2013) and Six Sigma (Parast, 2011), Enterprise Resource Planning (ERP) implementation (Ahmadi, Yeh, Martin, & Papageorgiou, 2015a) and RFID integration into shop floor operations (Chuang & Shaw, 2008). Companies are handicapped by low levels of 'innovation readiness' (Dutta et al., 2009). This means that they are lacking in many of the key elements required to create a successful platform for innovation. Companies may not reap the full benefits of their investments due to low levels of readiness to deploy their innovation initiatives. It is necessary to perform an assessment at the initial stage of implementing an innovation initiative with the purpose of identifying weaknesses or problems which may lead to failure. Questions such as how to deploy and when to deploy should be formally asked and answered prior to management committing to deploying an innovation initiative. Deployment readiness assessment is the focus of this paper. The rest of the paper is structured into four sections. First, the concept of deployment readiness in manufacturing is introduced. Second, a method for assessing deployment readiness is presented and this is followed by a simulation experiment that illustrates the proposed method. The paper ends with conclusion and suggestions for future work.

2. Deployment readiness concept in manufacturing

Attempts to deploy innovation initiatives in manufacturing fail because managers do not establish sufficient readiness for change. Following Jacobson's (1957) seminal work on the concept of readiness, the concept have been developed further including in manufacturing (e.g. Ahmadi et al., 2015a; Kwahk & Lee, 2008; Lim & Antony, 2013).

There are many different definitions of readiness and they cover several constructs such as organisational readiness and technology readiness. Organisational readiness generally refers to 'the extent to which organisational members are psychologically and behaviourally prepared to implement organisational change' (Eby, Adams, Russell, & Gaby, 2000). High levels of organisational readiness are likely to result in more effective implementation of a proposed change due to the inclination of members of the organisation to be cooperative, exhibiting greater effort and persistence towards implementing the intended change. On the other hand, low levels of organisational readiness present problems with members of the organisation likely to exhibit uncooperative behaviour, avoid or even resist actions that would result in more effective implementation of the proposed change. Parasuraman (2000) referred to technology-readiness constructs as 'people's propensity to embrace and use new technologies for accomplishing goals in home life and work'. These highlighted constructs bring out the challenges in deploying innovation in manufacturing, principally the complexity and uncertainty associated with the target organisation, the manufacturing technology and processes.

Retrospectively, readiness represents the extent to which an implementation has run smoothly and relatively problem free (Ahmadi et al., 2015a). It is a state of preparedness for something about to happen. In the specific case of implementing innovation, the benefits

of readiness in manufacturing include addressing potential risks at the early stages leading to better implementation that minimises unforeseen problems in production.

Implementing an innovation typically consists of three phases pre-implementation, implementation and post implementation and the readiness of an organisation to deploy innovation is an important issue in the pre-implementation phase. Pre-implementation is the time period prior to physical implementation and can invariably shape the attitudes of those charged with the implementation (Abdinnour-Helm, Lengnick-Hall, & Lengnick-Hall, 2003; Herold, Farmer, & Mobley, 1995). It is at the pre-implementation phase that the organisation prepares itself and develops the plans for deploying its innovation initiative. Extensive preparation before implementation is the key to success of implementing innovation initiatives and without proper readiness the implementation is likely to end in failure (Ahmadi et al., 2015a). Situating the concept of readiness in the pre-implementation phase allows for a more methodological approach to preparing for implementing innovation. A methodological approach suggested by Ahmadi et al., 2015a entails four main steps: (a) constructing a model for assessing readiness, (b) overall readiness level estimation of organisation, (c) analysing the level of readiness, and (d) improving the readiness level of the organisation providing a set of effective plans. Central to the methodology is knowing how to measure the degree of readiness which is fundamental to the other key issue of how to optimise the degree of readiness, so as to achieve the best possible implementation.

Measuring innovation readiness is important to ensure successful innovation outcome. Theoretically, a higher level of readiness to innovate will lower the risk of innovation failure which leads to more successful innovation outcome. The degree of readiness can be measured in an interval [0, 1] or in percentage points as [0, 100%]. A readiness measure close to 100% implies that there is an outstanding level of readiness to implement the innovation, meaning that the implementation should run smoothly and problem free. The problem of how to achieve the highest readiness degree, to implement an innovation initiative, is starting to be addressed. For example, regarding ERP systems, an organisation's readiness to implement ERP system is reported to be influenced by a variety of influential factors such as a clear project structure, clear implementation goals, availability of appropriate systems and procedures in the organisation, appropriate culture and structures associated with the ERP initiative, and an adequate level of support from human resources (Kwahk & Lee, 2008; Razmi, Sangari, & Ghodsi, 2009). The overall readiness estimate of an organisation is a function of the readiness estimates of the individual influencing factors. To model the interrelations between the individual influencing factors methods such as analytical network process (ANP) (Razmi et al., 2009), fuzzy cognitive maps inference (Ahmadi et al., 2015a), and a combination of fuzzy cognitive maps (FCMs) and the fuzzy analytical hierarchy process (FAHP) (Ahmadi, Yeh, Papageorgiou, & Martin, 2015b) have been used. A simulation approach to readiness assessment has been taken in this paper to more easily capture the complexities involved in modelling manufacturing processes and its operations. It is a powerful technique for analysing manufacturing systems (Mourtzis, Doukas, & Bernidaki, 2014) and, in general, for appraising innovation deployment strategies in organisations (Wang & Moon, 2013).

3. Assessing deployment readiness

The approach taken in this paper for the problem of assessing the deployment readiness of continuous innovation initiatives in manufacturing is to adopt a sequential decision process framework in which the manufacturing system evolves through transitions from one state to another. The transition is assumed to be influenced by the implementation of the continuously innovation initiatives. In this framework, continuous innovation involves multi-period decision problems in a planning horizon particularly a rolling period horizon in which decisions made in early stages are important with possible severe consequences for future stages. These situations are often characterised by uncertainty and the extent of its stage-wise resolution which may invoke a forward-looking behaviour of actors in the decision process (Qu, 2014).

It is further conceptualised in the framework adopted in this paper that the implementation is based on a deployment plan π that covers a pre-specified set of innovation initiatives. Given the deployment plan π, the problem is to assess the extent to which the plan will result in a smooth and problem-free deployment. This problem relates to plan assessment which seeks to find the probability of plan success i.e. that the plan achieves its goal or plan failure (Maier, Jain, Waldherr, & Sachenbacher, 2010). Given a probabilistic model M_{assess} that encodes the plant component behaviour and possible observations caused by concurrently executing a plan, the plan assessment problem is to compute a 'good' lower and upper bounds on the plan's success probability (Maier et al., 2010), i.e.:

$$p_l \leq P\big(G|O_{0:t}\big) \leq p_u \tag{1}$$

where G is the event that the plan π is executed successfully and $O_{0:t}$ are observations of the system.

In the context of deployment readiness assessment, G represents a reference point that is used for assessing a deployment plan and it is specified in terms of goal-achieving states. Each state in the manufacturing system will have a degree of readiness associated with it. For example, a state may have associated with it a set of features such as deployment influencing factors, or risks, that could degrade system performance and for which there is no appropriate mitigation provision in the deployment plan. Such states will result in a lesser degree of readiness compared to those whose features are entirely consistent with those that will deliver smooth and problem free deployment. Assume there are states $s \in S$ in the manufacturing system and that the states can be described by a set of features $X_1, X_2, \ldots X_N$ such that $s = X_1 \times X_2 \times \ldots \times X_N \in S$. In addition, assume there is a set of distinct configurations $c = \{c_1, c_2, \ldots c_z\} \in C$ of the features that will deliver smooth and problem-free deployment. This set of configurations c is the goal-achieving states. In this paper, M_{assess} is specified as a simulation model of the manufacturing system.

$$p_l \leq P\big(G|O_{0:t}\big) = \sum_{c_i \in c} P(c_i|O_{0:t}) \leq p_u \tag{2}$$

4. Simulation experiment

In this section, a simulation experiment consisting of a job shop is used to illustrate the approach developed.

4.1. Set up of the simulation experiment

The job shop scenario consists of 10 machines organised as in Figure 1. Each job must visit either Machine 9 or Machine 10 for quality assurance in addition to the operations performed on the job at some of the other machines. Jobs arrive into a pre-shop pool and await release according to a workload bounding release mechanism (Bergamaschi, Cigolini, Perona, & Portioli, 1997). Jobs are selected from the pre-shop pool on first-come first-served (FCFS) basis. The FCFS rule is also applied when sequencing the jobs for processing on machines. Jobs inter-arrival times are exponentially distributed with rate parameter set to 8 min.

Each job is assigned a random routing, i.e. a random machine visitation order with no machine being revisited. The following common assumptions are also adopted in this study. Each machine has a constant capacity throughout and the machines are always available. Set-up times are included in the operation processing times. The operation sequence for each job is uniformly distributed between 4 and 10 inclusive of visitation to either Machine 9 or 10. The operation times follow a uniform distribution between 10 and 50 mins on Machines 1–8 and between 10 and 40 mins on Machines 9 and 10. A job runs through all of its operations sequence. The due date of a job is internally determined using the total work-content (TWK) method (Blackstone, Phillips, & Hogg, 1982) with allowance factor of 5. Simulation starts with an empty shop and runs until 15,000 min. Data on the first 800 min are discarded to allow for a warm-up period and attainment of steady-state conditions.

Given this set-up, two sets of simulation experiments, A and B, were conducted and performance measures were: (a) machine utilisation and (b) delivery commitment measured as tardiness. Experiment A simulates the current set-up. In Experiment B, a deployment plan for a set of innovation initiatives is considered. The initiatives cover locally innovative and structural process innovations (Yamamoto & Bellgran, 2013). The innovations are: (a) integration of RFID into shop floor operations, and (b) replacement of Machines 9 and 10 with smart quality assurance stations. A phased deployment method is adopted as shown in Table 1, resulting in six states i.e. State 1 through to State 6.

The plan allows for the inspection machine to be replaced one at a time. When a quality assurance machine is offline, the operations that are sequenced for the machine are diverted to the alternative quality assurance machine that is operational. Processing times on the innovative quality assurance machines are much lower than the old machines, and it is derived from a uniform distribution with values between 2 and 5 mins. The implementation of the RFID starts at 4000 mins and have an immediate disruptive effect on the shop floor
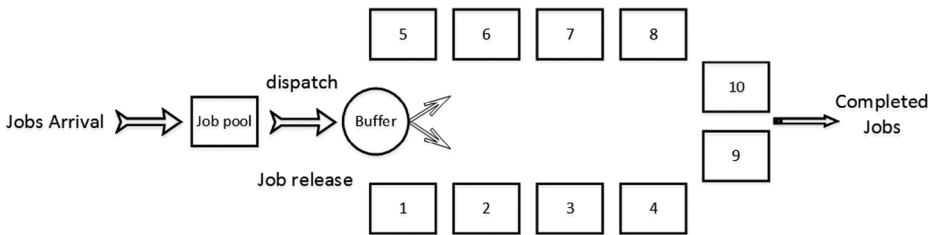

Figure 1. The simulated job shop.

Table 1. Deployment phases and states.

	Machine 9			Machine 10				Activity Times (mins.)	
	Old	Old	New	Old	Old	New			
State	Online	Offline	Online	Online	Offline	Online	RFID	Start	End
1	✓			✓					1500
2		✓		✓				1500	2000
3			✓	✓				2000	4000
4			✓	✓			✓	4000	4500
5			✓		✓		✓	4500	5000
6			✓			✓	✓	5000	

with a learning rate (Wright, 1936) of 80% that initially increases job processing times. This disruptive effect lasts up to 5000 min and from then onwards there is a reward for implementing the RFID with job processing times reduced by 25%.

4.2. Results and discussion

The results of experiments A and B are shown in Figure 2(a) and (b).

The utilisation levels shown in Figure 2(a) are lower following the implementation of the innovation initiatives. The replacement of Machine 9 has a considerably effect on utilisation, recording around 79% on average. This is expected and with the reduced utilisation levels the shop can accept more jobs from customers.

The delivery performance shown in Figure 2(b) indicates that when Machine 9 is offline, the delivery performance reduced considerably in terms of tardiness and there are more late jobs in comparison to the pre-deployment performance. The same applies when Machine 10 is offline although the reduction in performance is less considerable. This less considerable reduction in performance is due to the new Machine 9 that is online at the time Machine 10 is offline and during this period the reward from the RFID implementation is being accrued. The deployment plan thus has some merits in phasing out machine replacement. Post deployment of the initiatives, commencing from 6000 mins results in tardiness that is well below the pre-deployment values. The deployment readiness indices for the deployment states are shown in Table 2. The readiness goal specified is for job tardiness not to exceed 25mins. To calculate deployment readiness, via simulation, the number of jobs that are within this target is divided by the total number of jobs, for each of the deployment states.

The overall deployment readiness for the innovation initiatives based on the proposed deployment plan has a mean 88.31%. Accepting this level of readiness will depend on the Job shop's deployment readiness targets. For example, if the target is 92%, then improvements in the deployment plan will be necessary and deployment state 2 (mean readiness: 80.91%) and possibly deployment state 5 (mean readiness: 87.13%) amongst others would need to be considered for improvements. Recommendations for plan improvement could include hiring a quality assurance station for use while doing the Machine 9 and 10 replacements and implementing the RFID much earlier possibly before replacing Machine 9.
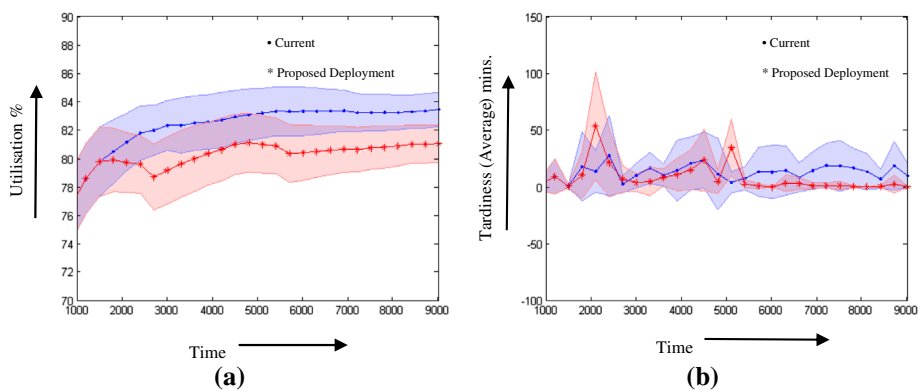
Figure 2. Simulation results: (a) Utilisation performance and (b) Delivery performance.

Table 2. Deployment readiness indices.

Deployment states	Deployment readiness indices (%)	
	Mean	Confidence level (95.0%)
2. Machine-9-OLD-Offline,machine-10-OLD-Online,RFID-NO	80.91	1.79
3. Machine-9-NEW-OnLine,machine-10-OLD-Online,RFID-NO	93.81	0.59
4. Machine-9-NEW-OnLine,machine-10-OLD-Online,RFID-YES	91.39	1.83
5. Machine-9-NEW-OnLine,machine-10-OLD-Offline,RFID-YES	87.13	1.29
Overall	88.31	0.87

5. Conclusions and future work

An approach to assessing deployment readiness of innovation in manufacturing has been explored in this paper. The assessment is done through simulation within a sequential decision process framework. Simulation offers advantages that include ability to model complex systems efficiently and effectively to obtain realistic assessments that takes into account uncertainties and dynamics inherent in the system. Given a manufacturing system with innovation initiatives, a deployment plan and deployment readiness goal(s), the approach first identifies the deployment states in the sequential decision process and calculates from simulation results a bound on the probability that the deployment plan will result in a smooth and problem-free deployment specified by the deployment readiness goal(s). The simulation experiment of a shop floor presented in this paper shows that deployment readiness can vary between deployment states and overall readiness can be improved by revising the deployment plan particularly in states where deployment readiness is relatively low. Future work should include a study of how deployment plan revisions can be best achieved.

Disclosure statement

No potential conflict of interest was reported by the authors.

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