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Building knowledge to improve enterprise performance from inventory simulation models

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ABSTRACT

This paper describes the process of building knowledge to improve enterprise performance. This allows managers both to identify unknown risks and to develop solutions that mitigate these risks. One of the most critical risks that the enterprise faces involves the unidentified presence of serial-correlation components on the demand patterns. Depending upon the levels of such correlation, inventory control policies can be appreciably inaccurate. We propose to use a knowledge management portfolio that allows managers to capture and build knowledge from their complex systems. We find that the error generated from ignoring identified risk factors exponentially grows as the autocorrelation increases. We construct an enhanced simulated annealing algorithm that provides superior solutions to this type of problem.

1. Introduction

Supply chain theory and practice suggest that an understanding of the dynamics of intricate and interrelated factors is necessary for a responsive and efficient supply chain. Successful enterprises recognize the impact these factors might exert on the organization's performance and understand the strategic value of well-designed and well-managed supply chains. Critical issues that remain uncovered may lead the firm to questionable performance. Discovering and addressing these issues become necessary to improve an enterprise's performance. To meaningfully consider these complexities, identify latent issues, and develop corrective action, it is necessary to employ a framework that allows managers to capture and transform information into usable knowledge. Knowledge Management (KM) emerges as a tool to identify risk issues and build usable knowledge that can provide substantial benefits to supply chain management (Drew, 1999).

The technology-based view of KM, as its name describes, involves approaches that identifies, generates, and distributes knowledge in an organization based on the use of technology. The type of knowledge considered in this paper resides in systems external to the human individual. An example of external information sources is the identification of risk patterns when analyzing a product's demand. Information systems that keep sales records are commonly the source of the raw data from which this knowledge is developed. This class of knowledge implies exploratory formation of new knowledge as opposed to the transfer of conventional knowledge within an organization (Alavi and Leidner, 2001). While operational knowledge is related to performing operations on a daily basis, strategic knowledge is fundamental to major decisions that capitalize on critical opportunities and effectively overcome major threats (Perrott, 2006, 2007). Discovering knowledge at either the operational or strategic level can represent an opportunity to enhance an enterprise's performance.

Control and inventory management is a critical area of the supply chain (Silver et al., 1998; Minner, 2003). The presence of dependency in stochastic demands, such as autocorrelation factors, is a risk factor in an inventory management system that may not be easily noticed (Charnes et al., 1995). If autocorrelation is not properly managed, then it may negatively impact supply chain performance. Positive auto-correlated demand has been identified as a factor that contributes to the negative consequences of the bullwhip effect (Kahn, 1987). The bullwhip effect is the consequence of demand variability amplification across all the stages of a supply chain. This demand distortion can generate difficulties along the supply chain such as incorrect demand forecast, sub-optimal capacity utilization, unnecessary inventory, and poor service levels (Lee et al., 2000).

The bullwhip effect, for example, occurs within strategic exchanges among the rational supply chain stages. The demand variance in supplier orders will be relatively greater than the variance observed in retailer orders or sales. This amplification of variance can mislead supply chain members in making inventory

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decisions that may result in losses. Lee et al. (1997) mathematically demonstrate that promotions can cause a bullwhip effect. They propose, in contrast to traditional promotion policies (e.g., Hi Lo), the use of everyday low pricing (EDLP) as an alternative pricing strategy. Wal-Mart, relative to the majority of the retailers, has seen success using the EDLP. Regardless of the specific approach, it can be said that most companies use price promotions to increase their market share and profits, though these promotions contribute to the bullwhip effect. This suggests the need for proper analysis of promotion mechanisms over other supply chain levers such as inventories. The generation of knowledge to address these bullwhip-related effects is reliant upon identifying the depth and frequency of the discount as well as the inventory policies.

The presence of autocorrelation components in stochastic demand has been studied in inventory control systems that assume backordering (Urban, 2000). Hausman and Erkip (1994) analyze the inventory of a major supplier of consumer products and discovered high levels of positive auto-correlated demands (approximately 0.7). In addition, Lee et al. (2000) analyze grocery store weekly sales data and find autocorrelations from 0.2 to 0.89. When demands are uncertain, stochastic inventory modeling provides techniques to characterize, analyze, and solve problems associated with optimal allocation of scarce resources. However, most of these techniques rely upon the assumption that demands are identically independent distributed (IID) (Biller and Ghosh, 2004). The assumption inherent in IID that is absent in the demand are dependency components (i.e., zero autocorrelation). Techniques that attempt to solve problems considering the IID assumption when these dependencies do exist can be misleading in their estimation (Melamed et al., 1992; Ware et al., 1998; Biller and Ghosh, 2004). These miscalculations may have substantial and significant consequences on enterprise issues such as facility and production planning. The IID assumption predominates in most analyzed inventory models. These models have been designed to aid inventory managers to build knowledge when demands are assumed not to contain dependencies. Deriving knowledge using an analytical framework to this class of problems can be very difficult due to complicated multivariate integration (Neter et al., 1990). In addition, inventory managers may face challenges recognizing and correctly representing auto-correlated demands while formulating a lost sale case.

A knowledge portfolio approach is considered in this paper to describe the process of building knowledge to improve a firm's performance. An opportunity to design appropriate policies that deal with these risk factors is analyzed. Appropriate tools are developed once a critical risk of this significance is discovered. These tools can be used to obtain control inventory policies that maximize the supply chain's efficiency. We use the knowledge portfolio described by Drew (1999) to illustrate the knowledge building process. The product analyzed in this context is produced and consumed in a competitive market. Unlike systems that accept backorders, the system considered in this analysis does not accept backorders. Customers that do not find what they are requesting in an electronic retail market, for example, most likely shop among other retailers. The unfulfilled demand is assumed lost for the retailer that is not able to supply the requested demand. Space and ordering restrictions also apply and constrain the amount of product available per period. A simulation-based optimization technique is used to consider such issues and approximate satisfying (sub-optimal) solutions. The inventory problem is characterized using a stochastic Dynamic Programming formulation. The simulation-based optimization is an enhanced version of simulated annealing that incorporates pattern search, and ranking and selection Diaz (2007). The impact of both ignoring and acknowledging this dependency component in the demand is quantified and analyzed.

This paper is organized as follows: first, the building knowledge process is presented within the inventory management context; second, the process of building knowledge process that begins with uncovering a risk factor until the problem is addressed is presented; next, empirical results are then analyzed; finally, a conclusion and managerial implications are provided.

2. The knowledge building process

The knowledge building process includes obtaining, transforming, implementing, and sharing knowledge based on information. Knowledge can be seen as a conclusion that is obtained from different data and information resources (Stewart, 2000). The process of building and managing knowledge in the enterprise can be described using the portfolio perspective suggested by Drew (1999). This model is constructed around the dimensions of knowledge content and awareness. It includes four types of business knowledge that are exhibited in Fig. 1.

The first quadrant illustrated in Fig. 1 shows the type of knowledge that is widely known and accessible in the enterprise. It can be summarized by the phrase: *what we know, we know*. Knowledge sharing, access, and inventory characterize this quadrant. Information can be stored in repositories and shared, for example, through intranets. The second quadrant refers to the class of existing knowledge that is available from data-gathering mechanisms. However, this knowledge might not be used and in many cases disregarded. This situation is described by the sentence: *what we know, we don't know*. The third quadrant addresses uncovering tacit knowledge. This can be encapsulated in the phrase: *what we don't know, we know*. Knowledge maps and training are among the techniques used in this level. Finally, quadrant four presents the knowledge that enables organizations to identify issues that may represent major threats or opportunities for the enterprise. This class of knowledge is summarized by the expression: *what we don't know, we don't know*. Audits are pointed out as means to discover key risk factors or potential business prospects that make possible the enterprise innovation.

The knowledge portfolio also can be seen as a mechanism to build and transform knowledge. For example, a potential risk for the enterprise and its inventory management may be the presence an auto-correlated component in the demand stream (type 4). This risk can be quantified and characterized as type 3. A simulation can be constructed to approximate solutions to this problem (type 2). Finally, other products can be analyzed using this meta-heuristic and the methodology resultant from these analyses (type 1). Advances in data collection and processing technologies provide opportunities to capture the behavior of complex variables and interactions with their environment. This knowledge can be used to formulate optimization and simulation models that can assist in the decision-making process. Both optimization and simulation models have been extensively used

Knowledge awareness	**1. What we know we know**	**2. What we know we don't know**
	3. What we don't know we know	**4. What we don't know we don't know**
	Knowledge content	

Fig. 1. Knowledge portfolio, Source—Drew (1999).