Expert Systems with Applications 41 (2014) 7005–7022

Contents lists available at ScienceDirect

Expert Systems with Applications

journal homepage: www.elsevier.com/locate/eswa

Application of a Fuzzy Feasibility Bayesian Probabilistic Estimation of supply chain backorder aging, unfilled backorders, and customer wait time using stochastic simulation with Markov blankets

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ARTICLE INFO

Article history:
Available online 27 May 2014

Keywords:
Supply chain
Decision support system
Bayesian network
Backorder
Fuzzy logic
Markov blanket

ABSTRACT

Because supply chains are complex systems prone to uncertainty, statistical analysis is a useful tool for capturing their dynamics. Using data on acquisition history and data from case study reports, we used regression analysis to predict backorder aging using National Item Identification Numbers (NIINs) as unique identifiers. More than 56,000 NIINs were identified and used in the analysis. Bayesian analysis was then used to further investigate the NIIN component variables. The results indicated that it is statistically feasible to predict whether an individual NIIN has the propensity to become a backordered item. This paper describes the structure of a Bayesian network from a real-world supply chain data set and then determines a posterior probability distribution for backorders using a stochastic simulation based on Markov blankets. Fuzzy clustering was used to produce a funnel diagram that demonstrates that the Acquisition Advice Code, Acquisition Method Suffix Code, Acquisition Method Code, and Controlled Inventory Item Code backorder performance metric of a trigger group dimension may change dramatically with variations in administrative lead time, production lead time, unit price, quantity ordered, and stock. Triggers must be updated regularly and smoothly to keep up with the changing state of the supply chain backorder trigger clusters of market sensitiveness, collaborative process integration, information drivers, and flexibility.

1. Introduction

The importance of supply chain management in today's military cannot be overemphasized. The Defense Logistics Agency (DLA) seeks to resolve a continually growing list of problem parts for the war effort and military readiness. It requires a streamlined and proactive approach to resolving problems with needed parts to reduce the long-term costs of maintaining the readiness of DLA-supported weapons systems. This paper presents an empirical study of the determinants of backorder aging for the Battlefield Breakout Backorder Initiative (B3I), a DLA supply chain system. We discuss the effects of the flow of material, information, and finance through the main supply chain agents of supplier, manufacturer, assembler, distributor, retailer, and customer.

DLA uses a multi-echelon supply system to make items available to the operational community. When this supply system is unable to satisfy demand, a backorder is created, indefinitely extending the customer wait time for that item. Backorder aging is affected by many factors associated with the item's demand and procurement history and by past support funding and the economics of suppliers. To improve the responsiveness of its supply system, DLA is seeking innovative, nontraditional ways of more quickly resolving backorders (and thus reducing customer wait time). DLA has created the B3I to research, develop, test, and evaluate policies, procedures, processes, tools, and methodologies to reduce the backorder aging problem for critical war-fighter supply items.

In addition, DLA is seeking ways to analyze supply chains as well as the factors that affect supply and demand to predict and address potential backorder problems before they occur. As part

Abbreviations: AAC, Acquisition Advice Code; ALT, administrative lead time; AMC, Acquisition Method Code; AMSC, Acquisition Method Suffix Code; B3I, Battlefield Breakout Backorder Initiative; BLS, birth to last shipment; CIIC, Controlled Inventory Item Code; COTS, Commercial Off The Shelf; DLA, Defense Logistics Agency; NIIN, National Item Identification Number; NP, Non-deterministic Polynomial-time; NSN, National Stock Number; PHDM, Procurement History Data Mart; PLT, production lead time; RHDM, Requisition History Data Mart; SCBORT, supply chain backorder trigger.

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http://dx.doi.org/10.1016/j.eswa.2014.05.012
0957-4174/

of this initiative, we developed a mechanism that can be embedded in the requisition process to identify items with a potential to become backordered, even before orders are placed. With this type of predictive tool available to them, DLA personnel are able to more efficiently and effectively address the problem of backorder creation, thus freeing up critical items for military personnel.

DLA supports the armed services by supplying a wide range of food items, medical items, construction and industrial materials, fuels and lubricants, clothing and textile items, and repair parts for weapons systems and associated equipment. When a military organization needs items, it requests (requisitions) them from DLA. DLA supports such requests by procuring and storing items in defense depots (stocking) and then shipping the items from the depots (issuing) to the organization requesting them or letting contracts with vendors who, when instructed by DLA, ship directly to the organization requesting the item. DLA thus manages more than 5.2 million items. Each day DLA responds to more than 54,000 requisitions, lets more than 8200 contracts, and performs contract actions such as delivery orders and modifications (Defense Logistics Agency, 2012).

To manage the procurement, stocking, and issuance of these 5.2 million items, DLA employs 21,000 people and uses an information technology system known as its Business System Modernization system. This system handles the full range of DLA business functions from procurement, to inventory management, to finance. DLA is not able to stock all items, and those items it does stock (or the items for which it sets up contracts for direct delivery) may not be fully stocked at levels that will satisfy all requisitions at any given time. This may be because of funding constraints or an inability to accurately forecast the demand for items. When DLA experiences stock outages (i.e., when a customer requisitions items but DLA is unable to fulfill all or even part of the requisition), that requisition is labeled as being "on backorder," which increases customer wait time. The total time necessary to procure and ship items can be broken down into two component times: the time needed to procure the item (administrative lead time [ALT]) and the time required to produce and deliver the item (production lead time [PLT]). Accurately predicting the total lead time (the sum of ALT and PLT) is as important to successfully maintaining inventory as predicting demand, particularly for replenishment items. The number of backorders is one key metric used by DLA to measure the performance of the order fulfillment aspect of its system and is monitored by the highest levels of management. Backorder reduction is thus a continued focus of attention from DLA management.

In this paper, we use real-world data to determine the structure of a Bayesian network. We then use stochastic simulation based on Markov blankets to determine the distribution of backorders. Fuzzy logic is used to produce a funnel diagram that demonstrates that the Acquisition Advice Code (AAC), Acquisition Method Suffix Code (AMSC), Acquisition Method Code (AMC), and Controlled Inventory Item Code (CIIC) backorder performance metric of a trigger group dimension may change dramatically with variations in ALT, PLT, unit price, quantity ordered, and stock. Triggers must be updated regularly and smoothly to keep up with the changing state of the supply chain backorder risk trigger (SCBORT) supply chain clusters of market sensitiveness, process integration, information drivers, and flexibility. The rest of the paper is organized as follows. In Section 2, we present the theoretical background and previous research on supply chain management. In Section 3, we describe the theoretical framework and hypotheses. In Section 4, we introduce the research design, data collection, and operationalization. In Section 5, we provide the results of the experiments. In Section 6, we conclude the paper with a summary and directions for future work.

2. Theoretical background and previous research on supply chain management

2.1. Research method and supply chain management

2.1.1. Research methodology

Backorder risk trigger evaluation of a supply chain is a complex task and research on this topic is still in its infancy. The significance of our research is that we are attempting to quantify the benefits of a Fuzzy Feasibility Bayesian Probabilistic Estimation model. This research method was the first to develop Fuzzy clustering to produce a funnel diagram that demonstrates that the Acquisition Advice Code, Acquisition Method Suffix Code, Acquisition Method Code, and Controlled Inventory Item Code backorder performance metric of a trigger group dimension may change dramatically. Because the choice of methodology is the most important factor necessary to identify the correct solution to a particular research problem, the collection and analysis of empirical data is being used in this research. Empirical data analysis will be beneficial to understand the role of the five trigger probability metric performance dimension groupings that include engineering issues, obsolescence issues, disruption of demand planning issues, NSN-specific unique sustainment problems, and cataloging issues in performance of the supply chain and the identification of backorder risk triggers. Our research methodology is employed to demonstrate that basic backorder information, such as the performance metric of a trigger group dimension, may change dramatically with variations in ALT, PLT, unit price, quantity ordered, and stock. Triggers must be updated regularly and smoothly to keep up with the changing state of the supply chain backorder risk trigger (SCBORT) supply chain clusters of market sensitiveness, process integration, information drivers, and flexibility. For this purpose, we have chosen to investigate 56,000 items from the Aerospace Industry. Our research method describes the structure of a Bayesian network from a real-world supply chain data set and then determines a posterior probability distribution for backorders using a stochastic simulation based on Markov blankets. Fuzzy clustering is used to produce a funnel diagram. To initialize the Bayesian network process, the basic mathematical approach used is outlined in Section 3.2.

A discussion of our contribution compared to the current relevant literature will be endeavored by making an explicitly clear list what is new in this study which has not been done by previous studies. Moreover, this list will make a direct connection between ESWA and our paper by clearly discussing the research contributions to ESWA-related works.

Our first contribution extends the work of Lee, Park, and Shin (2009) in which they used a Bayesian belief network to investigate risk in a large engineering project. Our paper extended the understanding of risk management by introducing trigger risk dimensions that may change dramatically and must be updated regularly and smoothly to keep up with the changing state of the supply chain.

A second contribution is introduced by a comparison with the study of Hanafizadeh and Sherkat (2009). Their fuzzy-genetic learner model allowed for the adaptation of plans to real conditions for decision making. Our paper extends this concept by introducing a fuzzy clustering algorithm that was used to produce a funnel diagram that demonstrates that the Acquisition Advice Code, Acquisition Method Suffix Code, Acquisition Method Code, and Controlled Inventory Item Code backorder performance metric of a trigger group dimension may change dramatically with variations in administrative lead time, production lead time, unit price, quantity ordered, and stock.

A third contribution involves the implications of cost in the supply chain. Gumus and Guneri (2009) contend that their fuzzy method presents minimum total supply chain cost values. Our paper's contribution to the literature is enhanced by the use of a real-world example from an aerospace database that presents a proposed fuzzy method that is independent of the membership functions used and is appropriate for use in situations in which assessment information may be qualitative, or precise quantitative information is either unavailable or too costly to compute. This fuzzy method of risk evaluation and group decision making in the presence of multi-echelon inventory management takes into consideration multiple dimensions and related multiple metrics, which is very useful for understanding and developing supply chain risk events and costs.

Tseng, Lin, Lin, Chen, and Tan (2014) use both hybrid fuzzy set theory and ANP methods and propose that by examining two types of methodologies it is easier to examine and study problems that have similar aspects and criteria with respect to situations that occur in a supply chain. Our paper adopts this philosophy and adapts it to describe the structure of a Bayesian network from a real-world supply chain data set and then determine a posterior probability distribution for backorders using a stochastic simulation based on Markov blankets. Our paper demonstrates that Stochastic simulation with Markov blankets can be applied to this supply chain problem. We used Bayesclust in the R Project for Statistical Computing and ran a simulation model for determining the posterior probabilities.

Jaipuria and Mahapatra (2014) suggest a method for improving demand forecasting and reducing bullwhip effect. This phenomenon is called the "bullwhip effect" because of the rippling panic that can occur in distribution channels when there is a real or perceived shortage of a product. Our paper extends this theory by demonstrating that there is a unique "bullwhip effect" at the DLA because the "war room" perceives a time delay (B3I) that does not exist at the operational level. In industry, such distribution quirks happen frequently, but they rarely trickle down to the consumer level. These largely psychological panics typically unwind when consumers regain confidence that supplies remain plentiful. At the DLA, the "war rooms" give false feedback that shortages exist, when in fact, the operational supply chain is robust.

Patil and Kant (2014) determined weights of the barriers as criteria, and a fuzzy method was used to obtain final ranking of the solutions of Knowledge Management adoption in SC. We build upon this theory in our paper because items with high wartime demand but low peacetime demand will naturally have some degree of pricing anomaly. Therefore, these results could change with the inclusion or exclusion of specific triggers or with the addition or removal of influential NSNs. However, this approach is beneficial insofar as it does not require any a priori knowledge management of the relationship among triggers or the underlying distribution of each trigger.

Ramanathan (2014) used actual industrial data and simulation to help managerial decision-making on the number of collaborating partners, the level of investments and the involvement in supply chain processes in order for supply chains to obtain maximum benefit of collaborative relationships. In our paper we outlined a process that allowed for the separation of data into identifiable groups that fit logically with the research model. The natural groupings consisted of four impact clusters or dimensions—market sensitiveness, collaborative process integration, information drivers, and flexibility—that can be measured by the five probability metrics of lead time, cost, quality, service level, and collaborative information availability.

Shu, Chen, Wang, and Lai (2014) examined the control of production disruption risk related to supply chain and investigated the uncertainty of production in supply chain enterprises for the purpose of achieving optimal profits in supply chain. Our paper lists five trigger probability metric performance dimension groupings including engineering issues, obsolescence issues, disruption of demand planning issues, NSN-specific unique sustainment problems and cataloging issues. We have reiterated the notion that the flexibility of SCBORT depends on the five dimensions of lead time, cost, quality, service level, and information availability. All five are essential to supply chain performance.

Kristianto, Gunasekaran, Helo, and Hao (2014) utilized a fuzzy shortest path to solve the problem complexity in terms of the multi-criteria of lead time and capacity with an efficient computational method. In our study, we examined data tables and fields available in Haystack. The Subject Matter Experts then determined the variables that would most likely affect lead times. Once those variables were determined, distinct NIINs were extracted from the RHDM/PHDM database and converted into a text file. The Batch function in Haystack was used to select the appropriate variables from the tables provided. The NIINs were then uploaded into Haystack, and all relevant variables were captured and downloaded into a Microsoft Access database in order to determine lead times.

Ferreira and Borenstein (2012) presented a novel method based on the integration of influence diagrams and fuzzy logic to rank and evaluate suppliers. In a similar manner our paper utilizes a fuzzy-Bayesian model for risk trigger selection. Our paper builds a case for the further improvement of importance grades or impact ratings, when evaluating the degree of SCBORT risk triggers, such as high ALT or PLT. If the risk trigger is too high, it may have to be improved. We believe that this fuzzy Bayesian assessment scheme should be used to determine the best improvements for SCBORT risk triggers. The model described in this study was based on expert consultation and interactive consensus analysis. Therefore, the evaluation results are more objective and unbiased than those of individual assessments.

Backorders, risk, and supply chain delays have all been studied extensively (Chuu, 2011; Gunasekaran, Patel, & Tirtiroglu, 2001). However, no study has used Fuzzy Feasibility Bayesian Probabilistic Estimation using stochastic simulation with Markov blankets to evaluate supply chain backorder risk. Shin, Shin, Kwon, and Kang (2011) noted that because of rapid changes in globalization, technical innovation, and competition, interdependence among operators in the supply chain has intensified. When one operator is exposed to even a small amount of risk, it is capable of disrupting the balance of the entire supply chain. Their paper used a Bayesian belief network to develop a framework of alternative backorder replenishment and to minimize total replenishment cost and expected risk cost. Blackhurst, Wu, and Craighead (2008) demonstrated that coordinating and managing distributed entities in a supply chain is challenging in part because of the conflicts present in such systems. They extended the concept of basic Petri nets to discover supply chain conflict before it occurred and had detrimental effects on system performance. Brijesh and Chandrasekharan (2011) determined the best installation inventory control policy or order policy parameters in a static divergent two-stage supply chain with one distributor and many retailers. They did this by using a genetic algorithm-based heuristic methodology to optimally solve problems over a large finite time horizon.

Huang, Axsäter, Dou, and Chen (2011) used compound Poisson demand to study the inventory system of an online retailer. Using real-time data on outstanding orders and customer wait times, they produced a decision rule for emergency orders that minimized expected costs under the assumption that no further emergency orders would occur. Liu, Kumar, and van der Aalst (2007) argued that as supply chains become more dynamic, there is a need for a sense-and-respond capability to react to events in real time. They proposed using Petri nets extended with time and color (to represent case data) to manage events, thus making very complex problems tractable. Chan and Chan (2010) argued that supply chains need to be flexible because they are subject to a variety of uncertainties, such as customer demand and supplier capacity. This is particularly true for make-to-order supply chains, whose material flow is triggered only by customer orders. These researchers used simulation to study how flexibility and adaptability in delivery quantity and due date can improve performance in a network of two-level multi-product make-to-order supply chains. Olsson and Tydesj (2010) developed a model with Poisson demand for a single-product and single-stock location in which the replenishment lead time from the external supplier was fixed, the lifetime of the product was also fixed, and aging was assumed to begin when the order was placed.

To show the importance of considering both dimensions of uncertainty in system modeling (i.e., stochastic variability and imprecision), Tüysüz and Kahraman (2010) used stochastic Petri nets together with fuzzy sets to model and analyze time-critical, dynamic, and complex systems. Toktas-Palut and Ulengin (2011) coordinated the inventory policies in a decentralized supply chain with stochastic demand by means of contracts and modeled a queuing system in which centralized and decentralized models were developed. Their comparison of the optimal solutions to these models revealed that the supply chain needs coordination. Bayındıra, Dekker, and Porras (2006) investigated the desired level of recovery under various inventory control policies when the success of recovery was probabilistic. Four inventory control policies that differed in timing and information were used in purchasing decisions with the objective of finding the recovery level and inventory control parameters that minimized the average total cost over the long run.

According to Mahadevan, Pyke, and Fleischmann (2003), sustainability has become a major issue in most economies, causing many leading companies to focus on product recovery and reverse logistics. Their research was focused on product recovery, in particular production control and inventory management in the remanufacturing context. They used a "push" policy that combined these two decisions. Yeh, Chen, and Chen (2011) argued that the mobility of popular goods on the shelves has a crucial impact on store sales and that to confirm the demand for a commodity, stores traditionally use a point-of-sale system to monitor inventory. To prevent monetary loss due to an information gap, they proposed the use of an intelligent service-integrated platform that uses the software agent as the framework to construct the integrated information system mechanism as well as uses radio frequency identification technology to realize the smart shelf as the trigger point for the retrieval of the commodity message. Gunasekaran and Ngai (2009) encouraged further research on the modeling and analysis of global outsourcing, optimization between product variants and the cost of production, the point of differentiation along the production/assembly process, the selection of suppliers, logistics costs, and customer relationship management.

Agarwal, Shankar, and Tiwari (2006) made the case that with the emergence of a business era that embraces change, manufacturing success and survival are becoming more and more difficult to ensure. They presented a framework that encapsulates market sensitiveness, process integration, information drivers, and flexibility measures of supply chain performance while exploring the relationship among lead time, cost, quality, and service and the leanness and agility of a case supply chain in a fast-moving consumer goods business.

Statistical analysis can help to model inventory and demand. It integrates these actions by investigating the inventory and demand processes owned by the nodes that stock items. This design provides much flexibility in understanding component stocking through the supply chain. The ultimate planning system may be run on a server or a personal computer, as Web-based planning applications have become a prominent source of software deployments (Kumar, 2001). The planning application domain is shown in Fig. 1.

Fig. 1 provides a graphic overview of the supply chain process based on independent nodes, although a supply chain does not exist without each of the nodes. Each node provides independent actions that interact with the actions of each of the other nodes that constitute the complete supply chain. Customers provide a "want" flowing from right to left. Each node to the left of the customer also provides a "want". The supplier provides a "need" flowing from left to right. Again, each node to the right of the supplier also provides a "need". The key to successful supply chain management is the uninterrupted flow of information.

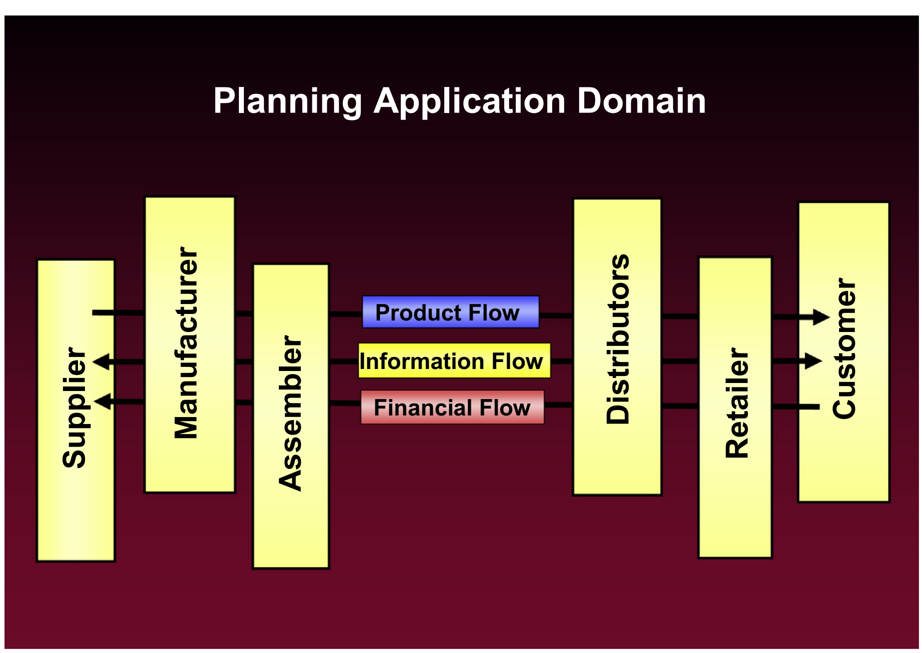

Fig. 1. Planning application domain.

3. Theoretical framework and hypotheses

3.1. Spiral development process

We used a spiral development process model to analyze the data and develop the mechanism to predict backorders and customer wait time. This model combines elements of both design and prototyping-in-stages to draw on the advantages of top-down and bottom-up concepts. It uses an iterative, incremental change approach. Also known as the spiral life cycle model, it is a systems development method used in information technology. This model of development combines features of the prototyping model and the waterfall model. It is intended for use in large, expensive, and complicated projects. We believe that the development of a predictive mechanism is technically feasible and in fact have identified more than one possible mechanism by which to accomplish the project goal.

The complexity of the DLA Supply Chain Research Initiative demanded the use of a superior analytical approach, first to investigate the feasibility of a predictive model and then to explore avenues that would lead to the development of that model. Throughout the project, we followed a rigorous analytical approach. First we drew from a relevant literature review, structured interviews, and brainstorming with DLA experts to hypothesize the major causes of backorder aging. Data were gathered, scrubbed, and analyzed using statistical techniques generally accepted in the industry, such as multiple regression analysis to determine probabilities. Using sensitivity analysis and Ishikawa diagrams, we investigated, conceptualized, and brainstormed to determine the component elements of ALT and PLT. These components included controlled inventory, AAC stock codes, AMSC Procurable Codes, Precious Metals Indicator Codes, Tech Documentation Codes, Item Standardization Code categories, Water Commodity Shipping Information categories, CIIC categories, and Criticality categories. By training with those data and investigating some baseline descriptive statistics, we discovered retrospective patterns in the data that supported the hypotheses that long ALT and long PLT lead to increased birth-to-last-shipment (BLS) dates. Once the feasibility of integrating data to develop a predictive mechanism was established, more sophisticated methods were required to provide actual prospective forecasting of backorder aging using B3I data. In order to accomplish this task, subject matter experts developed discrete numeric variables from the qualitative string characters present in the data set. First logistic regression analysis was used to find these prospective relationships. In a later iteration of the spiral development process, Bayesian networks used the discrete variables to determine the probabilities of these factors impacting BLS date, customer wait times, and logistic response times. Another iteration of the spiral development process may allow for the triangulation of the Bayesian probabilities with fuzzy logic and qualitative data to develop an expert system for B3I and backorder aging prediction.

The spiral development process of planning, analyzing, designing, and implementing a solution can be seen in our mechanism development methodology. We followed an iterative, incremental method of literature review, conceptualization, hypothesis development, descriptive statistical analysis, retrospective regression analysis, using discrete variables to run logit, and determining prospective Bayesian network probabilities. The next step in the spiral development process is to use this information to develop an expert system. Even with improved demand forecasting as a result of Commercial Demand Planning and the concurrent ability to reduce backorder aging caused by inaccurate forecasting, the process could be enhanced even further with the development of a process or mechanism for identifying which items have the probability of causing significant backorder aging. This leads to the following research question and resulting hypotheses:

Is there a feasible means of identifying items that will have a propensity not only to cause a backorder but also to cause backorders that remain unfilled over a long period of time (e.g., more than 240–360 days past their required delivery date)?

- H1: There is a relationship between ALT and backorder aging.
- H2: There is a relationship between PLT and backorder aging.
- H3: There is a relationship between unit price and backorder aging.
- H4: There is a relationship between quantity ordered and backorder aging.

3.2. Bayesian network development

Bayesian networks are one of the few techniques that allow a researcher to compute the posterior probability distribution of different nodes in a network. The exact algorithm for computing these posterior probabilities is computationally expensive and the task is Non-deterministic Polynomial-time (NP) hard (Cooper, 1990). Thus, approximation methods are often used. Among these approximation methods are stochastic simulation methods based on decision theory, Bayesian statistics, and Markov blankets (Henrion, 1986; Pearl, 1987). Bayesian networks have previously been used for prediction (Pendharkar, Subramanian, & Rodger, 2005; Stamelos, Angelis, & Sakellaris, 2003). Pendharkar et al. (2005) showed that Bayesian networks perform very well compared to other machine learning techniques. Previous studies on the application of Bayesian networks to supply chain data sets assumed that the causal structure of the Bayesian network was known or provided by an expert. Knowing the structure of a Bayesian network is not required, and there are sophisticated algorithms that can determine the structure of a Bayesian network from the data directly (Heckerman, 1997). Determining the structure of a Bayesian network from a data set is a computationally complex NP-hard problem as well (Hoffgen, 1993), but under certain restrictions of discrete variable values and no-missing values of variables, polynomial time algorithms can be used for this task (Cooper, 1992; Larranaga, Poza, Yurramendi, Murga, & Kuijpers, 1996). In this paper, we use real-world data to determine the structure of a Bayesian network. Then we use stochastic simulation based on Markov blankets to determine the posterior distribution of BLS date backorders when ALT, PLT, quantity ordered, unit price, and stock are known and when estimates for AMSC, AMC, AAC, and CIIC are available.

Constructing a Bayesian network is time consuming (Cooper, 1992). For moderately sized domains, a Bayesian network can be constructed by an expert or with the help of an expert (Cooper, 1992; Sarkar & Murthy, 1996). For large domains, or when no expert is available or only limited expertise is available, Bayesian networks are constructed directly from the data using advanced computing methods: local greedy search methods, global search heuristic methods, and information theory-based methods (Cheng, 1998; Cooper, 1992; Larranaga et al., 1996; Sarkar, Sriram, Joykutty, & Murthy, 1996). The local greedy search methods and global search heuristic methods use graph theory to construct a graph for the Bayesian network by adding and removing edges. The graph is constructed using a search algorithm and a scoring method that provides a score for each network structure. To manage the complexity of search, most of these algorithms assume that the information on node ordering is available (Larranaga et al., 1996). The approaches based on information theory do not assume that the information on node ordering is available and use information theory-based tests to check the strength of the relationships between variables before constructing the network. For problem domains with few variables, information theory-based approaches are better than local or global search approaches and produce superior network structures (Cheng, 1998). In real-world problem domains, information theory-based approaches have been successfully used on data sets containing hundreds of variables and millions of records (Spirtes, Glymour, & Scheines, 2000). Information theory-based approaches are suitable for constructing Bayesian networks using supply chain data sets because these data sets do not contain a lot of variables and the final network structure is important. The information theory-based approaches assume that all of the variables have discrete values and that there are no missing data in the database.

An information theory-based approach uses information flow measures, using mutual information and conditional mutual information metrics, to test whether two nodes are dependent on each other or independent of each other (Cheng, 1998). Assume that two nodes X and Y take discrete values in finite sets x and y. The mutual information metric $I(X, Y)$ for these two nodes is given as follows:

$$I(X,Y) = \sum_{x,y,} P(x,y) \log P(x,y)/p(x)p(y). \tag{1}$$

If another node Z takes discrete values in finite set z, then the conditional mutual information metric for X and Y conditioned on Z is defined as follows:

$$I(X,Y|Z) = \sum_{x,y,z} P(x,y,z) \log P(x,y|z)/p(x|z)p(y|z). \tag{2}$$

The independence of nodes X and Y is determined using an arbitrary threshold value of ξ. If $I(X, Y) \leqslant \xi$, then nodes X and Y are called marginally independent of each other. Furthermore, if $I(X, Y|Z) \leqslant \xi$, then nodes X and Y are called conditionally independent of node Z.

When an information theory-based algorithm is used to determine a Bayesian network from data, the input is an ordinary database table that contains discrete values and the threshold value of ξ, which is provided by the decision maker. For each pair of variables, the information theory-based algorithms compute mutual information. Then, using the values of the conditional mutual information and imposing certain graph model restrictions (directed acyclic graph and I-Map dependency), a Bayesian network is constructed. Once the Bayesian network is constructed, the parameters for the Bayesian network can be determined and stored in the form of prior and conditional probability tables.

The general problem of computing posterior distribution given partial evidence in a Bayesian network is an NP-hard problem. In most real-world situations, approximate methods are used that generate random variables according to the distributions associated with the variables in the network (Dean, Allen, & Aloimonos, 1995). The algorithms that generate the assignments by mimicking the distributions associated with the variables in the network are called stochastic simulation algorithms or Monte Carlo methods (Dean et al., 1995).

To better understand the application of stochastic simulation algorithm, consider the simple two-node network shown in Fig. 2. Assume that the variables A and B take two values, *true* and *false*. Furthermore, assume that the prior and conditional probabilities for variables A and B taking the value of *true* are known and given as shown in Fig. 2. If we are interested in finding the value of $P(B = true)$, then we can use stochastic simulation to compute this approximate value.

Assume a random number generator Rand(0, 1) that generates a random number between 0 and 1. We use this random number generator to generate two random numbers in each cycle. Assuming these two random numbers are stored in variables p and q, we can set the value of $A = true$ if $p \leqslant P(A)$, or $p \leqslant 0.3$ in our case. Next, assuming that A = true, if $q \leqslant P(B|A)$, then $B = true$. For all other cases, we assign the value of *false* to variable B. We repeat this procedure for a certain number of cycles, say *maximum cycles*, and then compute the approximate value of $P(B)$ as the number of times variable B was assigned the value of true divided by the value of variable *maximum cycles*. The pseudo-code for this procedure is shown in Fig. 3.

This approach is called a logic sampling approach (Henrion, 1986). In the case of large networks with multiple parents, Markov blankets are used with the logic sampling approach (Pearl, 1987). In the Markov blankets approach, a variable can determine its transition probability by inspecting only its parents, its children, and those nodes with which it shares children. Stochastic simulation based on Markov blankets proceeds as follows. First, assume that a Bayesian network with priors and conditional probabilities is available. Second, use a random number generator to produce a discrete value for each source variable using its prior probabilities. Third, proceed down through the network following the arrows and conditional probabilities to obtain the values of variables using the known values of their parents. Repeat the second and third steps a number of times and gather statistics. Finally, obtain the posterior probability for any event conditioned on any set of observed variables by dividing the frequency of the event observed in the simulation by the frequency of the set of observed variables that occurred in the simulation.

3.3. Sugeno fuzzy inference and fuzzy clusters

Fuzzy clustering has been applied to many decision-making problems, from auditing to financial management to strategic portfolio management to multi-objective decision making (Ammar, Wright, & Selden, 2000; Lin, Tan, & Hsieh, 2005; Yager, 1981). Researchers have proposed the use of a heuristic method for a resource-constrained project-scheduling problem with fuzzy activity times. This method was based on a priority rule for a parallel schedule generation scheme (Bhaskar, Pal, & Pal, 2011; Kao & Lin, 2011) that proposed that qualitative data be viewed as fuzzy numbers and that used data envelopment analysis multipliers associated with decision-making units being evaluated to construct membership functions.

The transition from the silo enterprise perspective to the process-based supply chain view of contemporary business has produced numerous benefits. Yet along with these benefits, new sources of risk have appeared because of the complex systemic nature of the supply chains. The need to reduce the increased

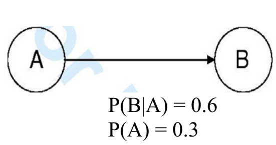

Fig. 2. A simple Bayesian network.

```
Total_B_true ← 0
Cycles ← 0

    Repeat
    p ← Rand(0,1)
    q ← Rand(0,1)
    Cycles ← Cycles + 1
    If p ≤ P(A) AND q ≤ P(B|A){Total_B_true ← Total_B_true + 1}
    If (Cycles ≥ Maximum_Cycles) Then Done

    Until Done
    P(B = true) = Total_B_true/Maximum_Cycles
```

Fig. 3. Pseudo-code for approximate inference using stochastic simulation.

vulnerability of the supply chain is a key research issue in supply chain management. Neiger, Rotaru, and Churilov (2009) proposed a novel value-focused process engineering methodology for process-based supply chain risk identification that increases the value to supply chain members and the supply chain as a whole.

To date, the vast majority of cluster analysis applications in operations management research have relied on traditional hierarchical and nonhierarchical methods. Although these methods continue to be used effectively in the operations management literature, Brusco, Steinley, Cradit, and Singh (2012) believe that there is a significant opportunity to expand the scope of clustering methods for operational risk assessments by supply chain professionals. They believe that emergent clustering methods in the operations management literature have implications for practice that traditional risk assessment methods do not.

The Sugeno, or Takagi–Sugeno–Kang, method of fuzzy inference was introduced in 1985 and is similar to the Mamdani method in many respects. The first two parts of the fuzzy inference process, fuzzifying the inputs and applying the fuzzy operator, are exactly the same. The main difference between Mamdani and Sugeno is that the Sugeno output membership functions are either linear or constant.

A typical rule in a Sugeno fuzzy model has the following form:

$$\text{If Input } 1 = x \text{ and Input } 2 = y, \text{ then Output is } z = ax + by + c. \tag{3}$$

For a zero-order Sugeno model, the output level z is a constant ($a = b = 0$).

The output level z_i of each rule is weighted by the firing strength w_i of the rule:

$$w_i = AndMethod\ (F_1(x), F_2(y)), \tag{4}$$

where $F_{1,2}(\cdot)$ are the membership functions for Inputs 1 and 2.

The final output of the system is the weighted average of all rule outputs, computed as

$$\text{Final Output} = \frac{\sum_{i=1}^{N} w_i z_i}{\sum_{i=1}^{N} w_i}, \tag{5}$$

where N is the number of rules.

The performance and impact Sugeno rule operates as shown in Fig. 12. The easiest way to visualize first-order Sugeno systems is to think of each rule as defining the location of a moving singleton. That is, the singleton output spikes can move around in a linear fashion in the output space, depending on what the input is. This also tends to make the system notation very compact and efficient. It is possible to build higher order Sugeno fuzzy models, but they introduce significant complexity with little obvious merit. Because of the linear dependence of each rule on the input variables, the Sugeno method is ideal for acting as an interpolating supervisor of multiple linear controllers that are to be applied, respectively, to different operating conditions of a dynamic nonlinear system. In the present study, fuzzy logic was used to produce a funnel diagram that demonstrates that the backorder performance metric of a trigger group dimension may change dramatically with variations in ALT and PLT. Triggers must be updated regularly and smoothly to keep up with the changing state of the SCBORT supply chain clusters of market sensitiveness, process integration, information drivers, and flexibility. A Sugeno fuzzy inference system is extremely well suited to the task of smoothly interpolating the linear gains to be applied across the input space; it is a natural and efficient trigger impact and probability performance scheduler. Similarly, a Sugeno system is well suited to modeling nonlinear systems by interpolating between multiple linear models and to illustrating the output of the process developed in this paper.

4. Research design, data collection, and operationalizations

This was a pilot outcomes study involving exploratory research. The first step was to brainstorm and conceptualize ALT and PLT constructs with their component parts. We obtained Requisition History Data Mart and Procurement History Data Mart (RHDM/PHDM) backorder data and embellished the existing National Item Identification Numbers (NIINs) with additional data from a Haystack database. We then analyzed those data using Ishikawa fishbone diagrams and affinity diagrams. We found that the elements that affected long ALT times were technical data, procurement history, source of supply, previous procurement practices, and buyers' workload. Long PLT times were caused by specifications, material, labor, and packaging. This led to the conceptualization of the ALT and PLT constructs, as well as their constituent items, as shown in Figs. 4–6. The resulting relational model is shown in Fig. 7.

Fig. 4 shows the affinity diagram interrelationships between the component factors of the ALT construct. Fig. 5 shows the Ishikawa fishbone diagram components of the ALT construct. These processes include sources, technical data, people, procurement history, regulations, and policies. Fig. 6 depicts the Ishikawa fishbone diagram components of the PLT construct. These processes include packaging, material, labor, and specification. Fig. 7 indicates the relationship among the three major dependent variables of backorder aging.

One of the major strengths of our research method was that we were contracted by the DLA because complaints on backordered items were quickly becoming problematic for the Department of Defense. Therefore, a second strength is that assessing and managing risk triggers is a real world problem that has become important for the enterprise to listen to and manage. Another of the strengths of our paper was that it analyzed risk triggers and proposed a novel approach via a Fuzzy Feasibility Bayesian Probabilistic Estimation model. The resulting Web Based decision support tool was used to improve this backorder dilemma. Another strength of the study was that we built the model based on Bayesian probabilities by monitoring and analyzing real-time items from the Aerospace Industry. We triangulated our method by utilizing regression analysis to study the feasibility of the study. The Bayesian network was developed from a real-world supply chain data set. We determined a posterior probability distribution for backorders using a stochastic simulation based on Markov blankets. Our research method was the first to develop Fuzzy clustering to produce a funnel diagram that demonstrates that the Acquisition Advice Code, Acquisition Method Suffix Code, Acquisition Method Code, and Controlled Inventory Item Code backorder performance metric of a trigger group dimension may change dramatically. We have demonstrated Construct Validity in our study, because we are reasonably sure that variations in administrative lead time, production lead time, unit price, quantity ordered, and stock impact backorders. Therefore, our proposed research method is strong because we have addressed the external validity issue that addresses generalizing the results of our study to other times, places, and persons. Our model should work as well in industry as It does in government settings. We also have the research method strength of correlational research because we accomplished our results by a variety of techniques, which included the collection of empirical data. The major weakness of the research method was the limitation of sample size. Although the original set of 11,000 real-world backorders appears to be a fairly large sample size, it only represents a subset of all of the possible combinations of known variables that may be observed in the real world. Increasing the sample size to include more real-world projects would result in fewer missing values in the conditional probability tables.

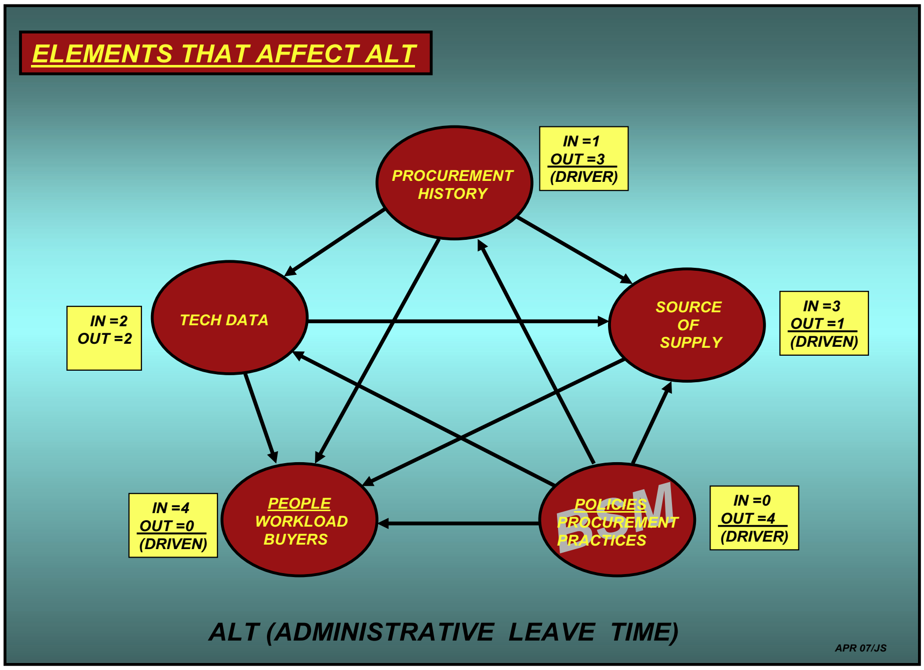

Fig. 4. Affinity diagram interrelationships between the component factors of the ALT construct.

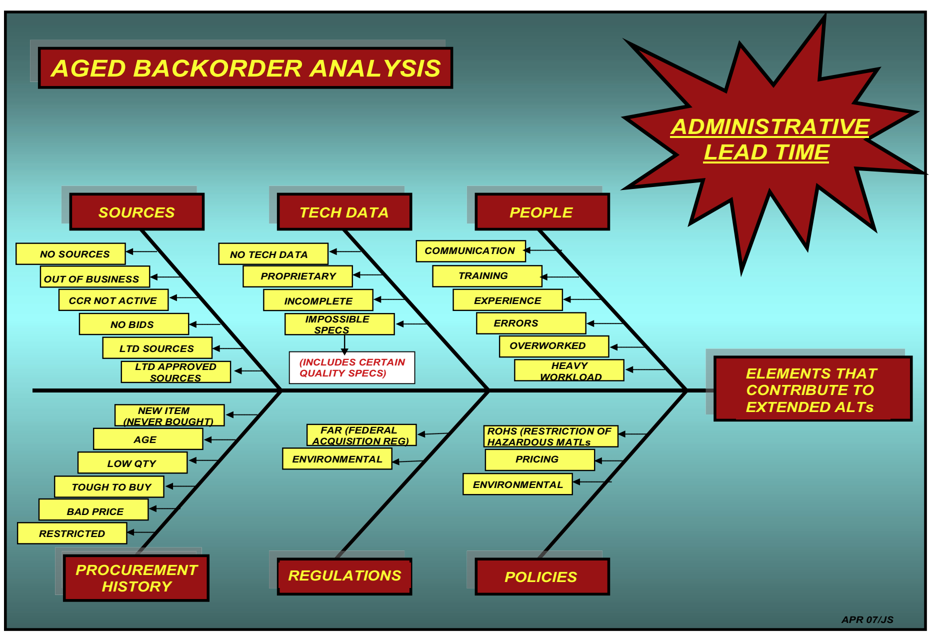

Fig. 5. The Ishikawa fishbone diagram components of the ALT construct.

5. Results

5.1. Overview: regression

The RHDM/PHDM data provided an adequate sample size and sufficient power for a multivariate regression test on backorder aging. We identified a set of factors that could be used to forecast backorder aging as measured in days. Using field data on backorders from various sources and the multiple regression model, we empirically tested the impact of ALT variables (which involve time to award the contract) and PLT variables (which lead to delays in vendor delivery). Drawing on the supply chain management literature, we deduced that these independent variables could be used to predict backorder aging in days as a dependent variable. The combined RHDM/PHDM data sets contained multiple NIINs, with 56,052 BLS entries. There were 1833 BLS entries $\geqslant$360 days and 48,136 BLS entries $\leqslant$90 days. Table 1 shows the means, standard deviations, and measures of statistical significance for quantity ordered, ALT, PLT, and unit price of the NIIN for both RHDM and PHDM for BLS entries $\leqslant$90 days and $\geqslant$360 days.

After we ran descriptive statistical analysis and graphically displayed the data in pie charts, we ran regression and Bayesian network analyses. The descriptive statistical analysis of the RHDM/PHDM databases led to several interesting conclusions. There

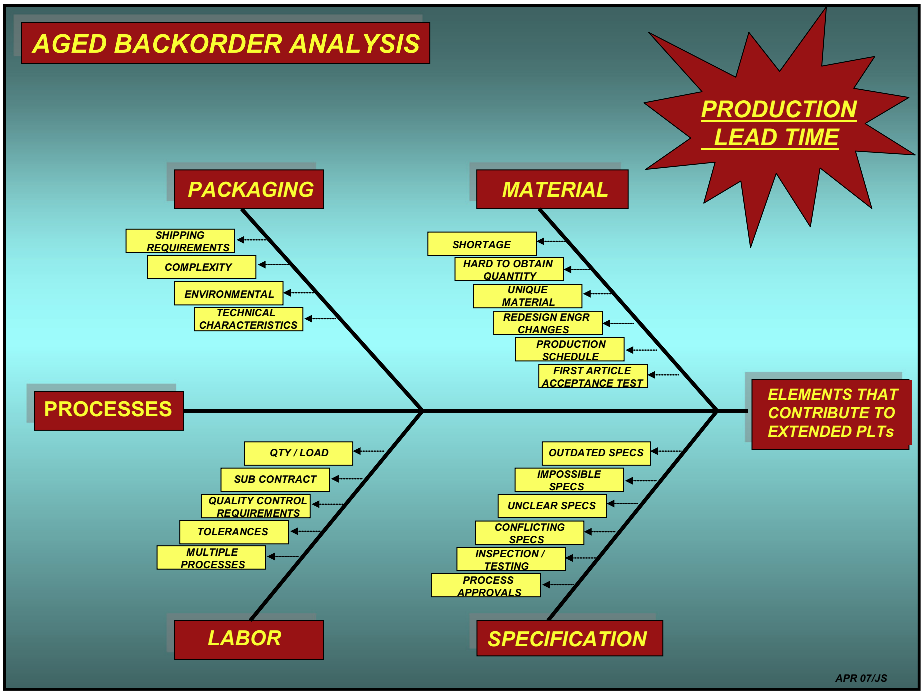

Fig. 6. The Ishikawa fishbone diagram components of the PLT construct.

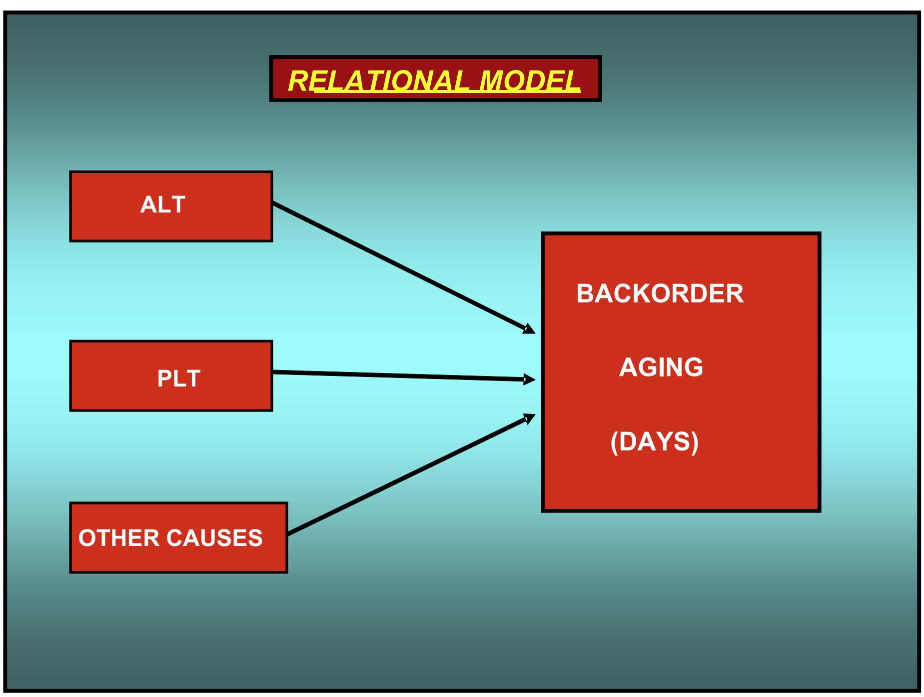

Fig. 7. The three major dependent variables of backorder aging.

Table 1
Descriptive statistics.

Backorder characteristic	⩽90 days			⩾360 days			p
	M	SD	N	M	SD	n	
Quantity ordered	19.47	207.91	48,136	21.31	111.40	1833	.947
ALT	3.85	9.86	48,136	45.53	107.99	1833	.001
PLT	8.83	15.68	48,136	40.16	60.82	1833	.001
RHDM unit price	408.67	2200.60	48,136	652.02	1821.07	1833	.001
PHDM unit price	880.11	12929.27	48,136	574.36	1611.31	1833	.001

was a statistically significant difference between NIINs with a BLS $\leqslant$90 days and those with a BLS $\geqslant$360 days for mean quantity ordered, ALT, PLT, and unit price. A majority of NIINs with a BLS $\leqslant$90 days were stocked items, whereas a majority of NIINs with a BLS $\geqslant$360 days were not stocked.

During the brainstorming sessions, we had hypothesized that stocked items (AAC codes D and H) would be less likely to be on backorder than items that were not stocked (AAC codes F, J, V, X, Y, Z). Discriminant analysis seemed to support this hypothesis. After the initial descriptive means comparisons were completed, discriminant analysis was used to examine the ability of ALT, PLT, unit price, and quantity ordered to accurately predict whether an item was stocked or not stocked. The analysis showed that ALT, PLT, unit price, and quantity ordered correctly classified AAC groups D and H approximately 77% of the time. Put another way, a long ALT, a long PLT, a high unit price, and a high quantity ordered increased the likelihood of an item being classified as not stocked. The overall discriminant model was statistically significant ($p \leqslant .001$). In addition to descriptive statistics, predictive statistics were applied to the RHDM/PHDM data set. Tables 2–4 show that approximately 40% of the BLS was explained by the independent variables quantity ordered, ALT, PLT, and unit price. The overall model was significant ($p \leqslant .000$). This indicates that there may be a relationship between BLS date and ALT, PLT, quantity ordered, and unit price. However, quantity ordered did not contribute to the significance of the relationship ($p = .957$). AAC codes D and H (stocked) had an inverse relationship with BLS date. Therefore, items that are in stock take less time to ship. Table 5 provides the classification results of the discriminant analysis.

5.2. Bayesian outcomes

Although the initial regression analysis showed promising results, ALT and PLT pose several problems for researchers seeking to develop a mechanism to predict long lead times. This is primarily because ALT and PLT are aggregate constructs. In essence, they reflect the total time spent procuring and producing a product. As the regression analysis results revealed, they are excellent retrospective indicators of long lead times. However, to predict backorders prospectively, perhaps for a new NIIN with no historical ALT and PLT data, it is crucial to examine individual component variables that are likely to increase the two measures of lead time. Therefore, we explored the potential of using a commercially available software product, Haystack, to determine variables that would affect ALT and PLT. After examining the data tables and fields available in Haystack, the Subject Matter Experts determined the variables that would most likely affect lead times. Once those variables were determined, distinct NIINs were extracted from the RHDM/PHDM database and converted into a text file. The Batch function in Haystack was used to select the appropriate variables from the tables provided. The NIINs were then uploaded into Haystack, and all relevant variables were captured and downloaded into a Microsoft Access database to determine lead times. Once that information was placed in Access, a query was run in each table to eliminate multiple NIINs. We then created a universal table from the individual Haystack tables, and the BLS data that had been acquired from the RHDM/PHDM information were integrated into the main table. Once the data were extracted from Haystack and cleaned in Access, they were exported to SPSS, a commercial statistical analysis program. Once in SPSS, all variables were recoded from text format to numerical format to allow for data analysis. Based on recommendations by Subject Matter Experts, each variable was categorized to reflect logical groupings of indicator codes. For example, the Document Availability Code originally consisted of 16 possible alpha and numeric code values. Team members determined that these 16 codes could be grouped logically into four major categories. This process was repeated for all variables extracted from Haystack. Table 6 shows the categories we assigned to the variables downloaded from Haystack.

However, the model was only able to classify 5% of backordered NIINs correctly. This is most likely because of rare population effects. Because the sample consisted of an overwhelming number of non-backordered items relative to backordered items, it was possible by random chance to have several non-backordered NIINs with attributes similar to those of backordered NIINs. The net effect was to mask any significant differences. Had more data been gathered and a greater number of predictor variables been available for analysis, it is likely that the predictive ability of this model would have increased. Because additional variables were not available, we turned to a Bayesian analytical model. Bayesian models differ from inferential statistics, such as logistic regression, in what they predict. Inferential statistics use algorithms to compute the effect that each variable has on a dependent variable. In the case of logistic regression, exp(B) is the effect size and backorder is the dependent variable. With inferential statistics, problems such as rare populations and non normal probability distributions can limit the effectiveness of a model. Bayesian models, in contrast, estimate uncertainty. That is, Bayesian models estimate a conditional probability, which in this study represents the probability that an item will be on backorder based on the probability of other occurrences. In the case of the logistic regression model that we used, several of the predictor variables were significant, but the model was unable to accurately classify NIINs as backordered or not backordered. Thus, we determined that a better approach would be to estimate the conditional probability of being backordered as opposed to classifying each NIIN as backordered or not backordered. Furthermore, Bayesian models are not as sensitive as inferential statistics to rare populations, so we postulated that a Bayesian model might be a better fit for the data. We used use real-world data from DLA to determine the structure of the Bayesian network. A future application may be to use stochastic simulation based on Markov blankets to determine the posterior

Table 2
Model summary.

Model	R	R^2	Adjusted R^2	SE of the estimate
1	.632[a]	.399	.399	74.495

[a] Predictors: (Constant), acc, unitpric, dodaqua, plt, alt.

Table 3
Analysis of variance.[a]

Model		Sum of squares	df	Mean square	F	Sig.
1	Regression	167208649.596	5	33441729.919	6026.037	.000[b]
	Residual	251621659.606	45341	5549.539		
	Total	418830309.203	45346			

[a] Dependent variable: birtolas.
[b] Predictors: (Constant), acc, unitpric, dodaqua, plt, alt.

Table 4
Coefficients.[a]

Model		Unstandardized coefficients		Standardized coefficient	*t*	Sig.
		B	*SE*	B	*B*	*SE*
1	(Constant)	18.407	.730		25.205	.000
	plt	1.032	.010	.400	104.978	.000
	alt	1.114	.011	.389	99.145	.000
	unitpric	.000	.000	.010	2.797	.005
	dodaqua	8.31E−005	.002	.000	.054	.957
	acc	−2.806	.806	−.013	−3.483	.000

[a] Dependent variable: birtolas.

Table 5
Classification results.[a,b]

		Acc	Predicted group membership		Total
			0	1	0
Original	Count	0	5095	7862	12957
		1	2760	29630	32390
		Ungrouped cases	76	6715	6791
	%	0	39.3	60.7	100.0
		1	8.5	91.5	100.0
		Ungrouped cases	1.1	98.9	100.0
Cross-validated[a]	Count	0	5092	7865	12957
		1	2772	29618	32390
	%	0	39.3	60.7	100.0
		1	8.6	91.4	100.0

[a] Cross-validation is done only for those cases in the analysis. In cross-validation, each case is classified by the functions derived from all cases other than that case.
[b] 76.6% of the original grouped cases were correctly classified.

distribution of factors such as controlled inventory, AAC stock codes, AMSC Procurable Codes, Precious Metals Indicator Codes, Tech Documentation Codes, Item Standardization Code categories, Water Commodity Shipping Information categories, CIIC categories, and Criticality categories given the known values of BLS date, customer wait time, and logistic response time. The naïve Bayesian model is shown in Fig. 8.

We used Belief Network Power Soft software and input from several Subject Matter Experts (SMEs) to produce the Bayesian network. However, Belief Network Power Soft software does not have the functionality to obtain all of the data needed to produce the prior and conditional probability tables of a Bayesian network. To produce the prior and conditional probability tables for the Bayesian network shown in Fig. 8, we exported the data into Microsoft Excel and used the software's data-filtering capabilities for the data analysis. Tables 7–15 report the prior and conditional probabilities for the Bayesian network shown in Fig. 8. As mentioned previously, the sample size was approximately 11,000 distinct NIINs.

Tables 7 and 8 describe the prior and conditional probabilities of the CIIC factor. This factor is composed of three categories: arms, classified, and pilferable. As Table 7 indicates, there is a 97% prior probability that a NIIN will be in the classified category, a 2.5% chance it will be arms, and a 0.5% chance it will be pilferable. Table 8 classifies the three CIIC factors by BLS date ⩽90 days, 91–359 days, and ⩾360 days, with the respective conditional probabilities.

Tables 9 and 10 describe the prior and conditional probabilities of the AMC factor. This factor is composed of three categories: direct acquisition, competitive acquisition, and Commercial Off The Shelf (COTS) direct. As Table 9 indicates, there is a 42.4% prior probability that a NIIN will be in the direct acquisition category, a 29% chance it will be competitive, and a 28.6% chance it will be COTS/direct. Table 10 classifies the three AMC factors by BLS date ⩽90 days, 91–359 days, and ⩾360 days, with the respective conditional probabilities.

Tables 11 and 12 describe the prior and conditional probabilities of the AMSC factor. This factor is composed of three categories: procurable, limited procurement, and not established. As Table 11 indicates, there is a 36.6% prior probability that a NIIN will be in the procurable category, a 34.8% chance it will be limited procurement, and a 28.6% chance it will be not established. Table 12 classifies the three AMSC factors by BLS date ⩽90 days, 91–359 days, and ⩾360 days, with the respective conditional probabilities.

Tables 13 and 14 describe the prior and conditional probabilities of the AAC factor. This factor is composed of two categories: stocked and not stocked. As Table 13 indicates, there is a 49.1% prior probability that a NIIN will be in the stocked category and a 50.9% chance it will be not stocked. Table 14 classifies the two AAC factors by BLS date ⩽90 days, 91–359 days, and ⩾360 days, with the respective conditional probabilities.

Table 15 gives the conditional probabilities for several representative variables (i.e., CIIC, AMC, AMSC, AAC, and BLS date) and their associated categories. The probability of a BLS date ⩽90 days ranged from a low of 62.6% (for NIINs in the arms, competitive, limited procurement, not stocked categories) to a high of 74.5% (pilferable, direct, procurable, stocked). The Bayesian network indicated that the probability that a NIIN would be subjected to backorder aging of ⩾360 days ranged from a low of 4.25% (pilferable, direct, procurable, stocked) to a high of 5.73% (arms, competitive, limited procurement, not stocked). Similarly, the probability that a NIIN would be subjected to backorder aging of 91–359 days ranged from a low of 21.25% (pilferable, direct, procurable, stocked) to a high of 32.1% (arms, competitive, limited procurement, not stocked).

Because CIIC has three categories, AMC has three categories, AMSC has three categories, AAC has two categories, and BLS date has three categories, there are 162 unique possible combinations of these variables. It is not necessary that all unique combinations be observed in the real world, but the 11,000 projects available to us represented only a small subset of these combinations. As a result, the conditional probability tables contain some missing values. Estimating BLS date backorders when ALT, PLT, quantity ordered, unit price, and stock are known and when estimates for

Table 6
Categories assigned to the variables downloaded from Haystack.

Haystack variable	Categories
Document Availability Code	Technical documentation available Technical documentation unavailable Technical documentation fully accessible Limited accessibility to technical documentation Document Availability Code missing
Criticality Code	Non-critical non-nuclear-hardened part Critical feature or nuclear-hardened part Criticality information not available
AAC	Not stocked at depot level Stocked part (codes D and H)
CIIC	Arms item Classified item Pilferable item CIIC not available
AMC	Direct acquisition Competitive acquisition COTS or direct vendor acquisition
AMSC	Procurable Limited procurement COTS/direct vendor/not established
Item Standardization Code	Authorized for procurement Not authorized for procurement
Status Code	Active and unrestricted NIIN Restricted or canceled NIIN
Precious Metals Indicator Code	Part manufactured with precious metals Part manufactured without precious metals
Water Commodity Shipping Information	NIIN classified as chemicals, ammo, arms, or instruments All other NIINs

AMSC, AMC, AAC, and CIIC are available constitutes a posterior distribution estimation problem. Stochastic simulation with Markov blankets can be applied to this problem. We thus used Bayesclust in the R Project for Statistical Computing and ran a simulation model for determining the posterior probabilities as shown in Fig. 9. The posterior probabilities for CIIC and BLS date are shown in Table 16.

5.3. The Sugeno method of fuzzy inference and trigger risk identification

A National Item Identification Number (NIIN) is a 9-digit numeric code which uniquely identifies an item of supply in the NATO Codification System (NCS). The NIIN is often prefixed by the Supply Class to form a NSN. However, the NIIN alone uniquely identifies the item, the FSC merely adds context by indicating the general classification of the item (Defense Logistics Agency, 2012 <http://www.dla.mil/dla_pubsite/about_dla.aspx>).

A primary objective of identifying SCBORT was to group or sort the National Stock Numbers (NSNs) analyzed into logical groupings, or *buckets*. The project team was tasked with creating or determining groups of triggers for subsequent analysis. One promising statistical inference technique for grouping triggers into homogenous subsets is variable cluster analysis. This technique is used to explain the dimensionality of a set of data by creating hierarchical sets of clusters based on a matrix of distances or, alternatively, similarities. Put simply, the procedure groups triggers into increasingly similar clusters. The result is a dendrogram that allows a user to visualize the relationship among the triggers—in other words, to see which triggers occur together most often. Using this graph, one may select an acceptable level of similarity or difference, drawing a horizontal line to indicate how many clusters or groups the triggers form.

The triggers in this study clustered into two distinct groupings; several triggers appeared to function independently but could be logically placed into three clusters. Both groupings were intuitively logical. One group contained Triggers 2, 6, 7, and 11. Items that have not been purchased recently (Trigger 2) will generally have an eroded supplier base (Trigger 11). This leads to the availability of insufficient technical data (Trigger 6), which increases ALT and PLT (Trigger 7). The other major group included Triggers 8, 16,

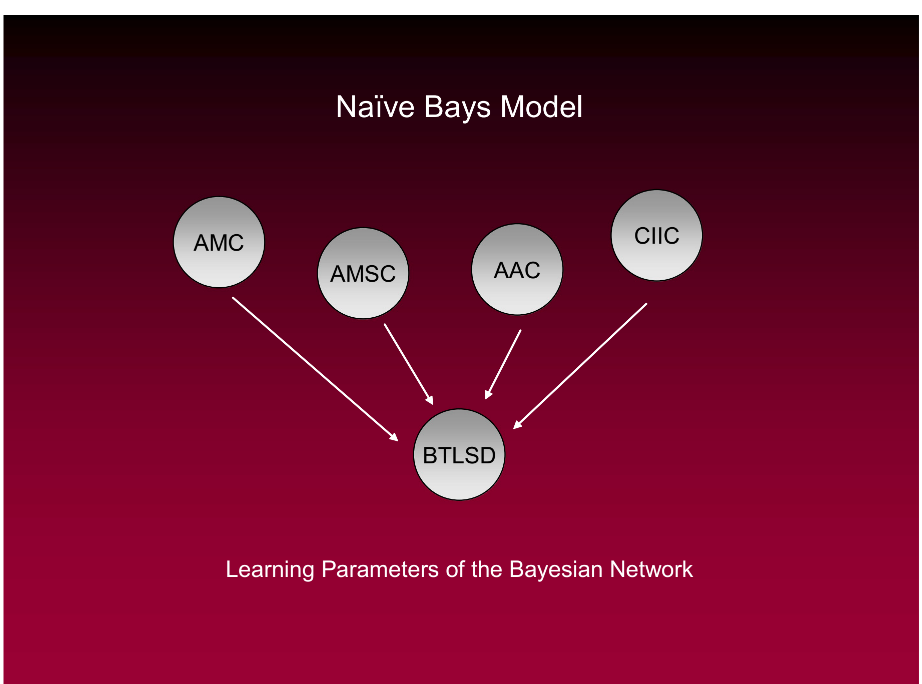

Fig. 8. The naïve Bayesian model.

Table 7
CIIC prior distribution.

CIIC	Prior probability
Arms	0.025
Classified	0.97
Pilferable	0.005

Table 8
CIIC and BLS date conditional probability.

CIIC	BLS ⩽90	BLS = 91–359	BLS ⩾360
Arms	0.637	0.308	0.055
Classified	0.676	0.274	0.050
Pilferable	0.787	0.164	0.049

Table 9
AMC prior distribution.

AMC	Prior probability
Direct acquisition	0.424
Competitive acquisition	0.290
COTS/direct	0.286

Table 10
AMC and BLS date conditional probability.

AMC	BLS ⩽90	BLS = 91–359	BLS ⩾360
Direct acquisition	0.693	0.259	0.047
Competitive acquisition	0.657	0.292	0.052
COTS/direct	0.670	0.278	0.051

Table 11
AMSC prior distribution.

AMSC	Prior probability
Procurable	0.366
Limited procurement	0.348
Not established	0.286

Table 12
AMSC and BLS date conditional probability.

AMSC	BLS ⩽90	BLS = 91–359	BLS ⩾360
Procurable	0.701	0.256	0.042
Limited procurement	0.655	0.290	0.055
Not established	0.670	0.278	0.052

Table 13
AAC prior distribution.

AAC	Prior probability
Stocked	0.491
Not stocked	0.509

and, to a lesser extent, 10a. Items that are heavy maintenance/wear NSNs (Trigger 8) will generally see an increase in demand during wartime. Some of these items will also have low peacetime demand, which qualifies them for the Warstopper Surge & Sustainment program (Trigger 16). Moreover, items with high wartime demand but low peacetime demand will naturally have some degree of pricing anomaly (Trigger 10a).

Table 14
AAC and BLS date conditional probability.

AAC	BLS ⩽90	BLS = 91–359	BLS ⩾360
Stocked	0.802	0.167	0.032
Not stocked	0.555	0.378	0.067

Table 15
CIIC, AMC, AMSC, AAC, and BLS date conditional probabilities.

CIIC, AMC, AMSC, AAC	BLS ⩽90	BLS = 91–359	BLS ⩾360
Arms, direct, procurable, stocked	0.7082	0.2475	0.0443
Arms, direct, limited, stocked	0.6968	0.256	0.0483
Arms, direct, COTS/direct, stocked	0.7005	0.253	0.0465
Arms, competitive, limited, not stocked	0.62.6	0.321	0.053
Pilferable, direct, procurable, stocked	0.745	0.2125	0.0425

```
≥ load("C:\\Users\\James\\Documents\\Fall 2013\\JOM\\.RData")
≥ # generate random 2-variable data
≥ Y ≤- matrix (rnorm(24), nrow=12)
≥ #search for optimal partitioning of data into 2 clusters
≥ test1 ≤-cluster.test(Y, p=2, nsim=2000, replications =3)
Replication 1 done
Replication 2 done
Replication 3 done
≥ # summary output
≥ summary(test1)
Cluster test conducted on data object data1, with 2000 iterations
********************************
Final Empirical Posterior Probabilities
********************************
Post Probs
Rep1    0.3316
Rep2    0.2604
Rep3    0.3281
```

Fig. 9. Posterior probabilities.

Table 16
CIIC and BLS date posterior probabilities.

CIIC	BLS ⩽90	BLS = 91–359	BLS ⩾360
Arms	0.6284	0.3316	0.0400
Classified	0.6946	0.2604	0.0450
Pilferable	0.6369	0.3281	0.0350

Of course, these results could change with the inclusion or exclusion of specific triggers or with the addition or removal of influential NSNs. However, this approach is beneficial insofar as it does not require any a priori knowledge management of the relationship among triggers or the underlying distribution of each trigger. This technique can also be extended to more conventional hierarchical cluster analysis, in which cases (NSNs) are grouped into increasingly similar clusters based on their status for a particular set of triggers. With a large number of NSNs, this can be both computationally intensive and difficult to interpret. Therefore, nonsensical triggers are dropped from the bucket list.

Cluster analysis can also be used to find natural groupings of data. Specifically, factor analysis is used to assign multi-sensor data to clusters based on factor loadings. In accordance with the five basic steps required for a cluster algorithm, the sample data were selected, a set of variables to measure was defined, the similarities among the entities were computed, factor analysis was used to create similar groups, and the resulting cluster solution was validated. This process allowed for the separation of data into identifiable groups that fit logically with the research model. The natural groupings consisted of four impact clusters or dimensions—market sensitiveness, collaborative process integration, information drivers, and flexibility—that can be measured by the five probability metrics of lead time, cost, quality, service level, and information availability (Zhou, Chen, & Liu, 2011). The count of NSNs by trigger is shown in Table 17.

Using the Sugeno fuzzy logic procedure, project team members discussed grouping trigger outputs, resulting in the development of a set of priorities for the establishment of trigger output buckets. This set of priorities reflected the problem part workflow. The group then developed a list of five trigger probability metric performance dimension groupings:

- engineering issues
- obsolescence issues
- disruption of demand planning issues
- NSN-specific unique sustainment problems
- cataloging issues

This clearly shows that the flexibility of SCBORT depends on the five dimensions of lead time, cost, quality, service level, and information availability. All five are essential to supply chain performance. These dimensions must be balanced and improved depending on the industry to which the supply chain belongs and the strategy it implements. When only the collective evaluation result of SCBORT is considered, information from one dimension may submerge that of another. The present study proposes a scheme for evaluating the degree of SCBORT, thus enabling decision makers to judge the need to improve SCBORT and determine the dimension of SCBORT that most urgently requires improvement. Furthermore, SCBORT can be evaluated using the evaluation schematics discussed previously. The assessment scheme comprises three main stages. The first stage evaluates the degree of improvement with respect to each backorder risk trigger dimension metric. The second stage evaluates the degree of improvement with respect to SCBORT clusters. Finally, the third stage involves the use of interactive consensus analysis to make a consistent decision via the fuzzy approach.

The rules input and output membership functions are shown in Figs. 10–13. Figs. 10 and 11 show the inputs of ALT and PLT. Fig. 12 shows the nine rules generated. Fig. 13 provides the BLS date output. Fig. 14 uses a funnel diagram to demonstrate the relationship between ALT, PLT, and BLS date.

6. Conclusions, recommendations, discussion, and future research

6.1. Conclusions and recommendations

Several conclusions can be drawn from this analysis of the PHDM and RHDM databases. For example, the combined RHDM and PHDM data sets contained 56,052 BLS entries. Of these, 1833 entries were BLS $\geqslant$360 days and 48,136 were BLS $\leqslant$90 days. There was a statistically significant difference in quantity ordered, ALT, PLT, and unit price between BLS $\leqslant$90 days and $\geqslant$360 days. Histograms provided visual support for these conclusions and suggested that the profiles of the $\leqslant$90 day sample and the $\geqslant$360 day backorders were distinctly different. A majority of the AAC groups fell into the D, H, J, and Z categories for both $\leqslant$90 and $\geqslant$360 days. For both BLS $\leqslant$90 days and $\geqslant$360 days, Groups 1 and 3 accounted for a majority of the AMC groups, whereas C, G, H, and P were the major AMSC groups. Pie charts supported these conclusions.

Discriminant analysis also provided some interesting insights. For example, ALT, PLT, unit price, and quantity ordered correctly classified ACC groups D and H approximately 77% of the time. The overall model was significant at $p = .000$. Therefore, if the ALT, PLT, unit price, and quantity ordered is known, a buyer can use this model to predict whether the item is stocked or not stocked and order accordingly. In analysis of variance, the model was significant at $p = .000$. Regression analysis supported the hypotheses that there was a possible relationship between ALT, PLT, and ACC code and BLS date ($p = .00$). There was also support for the hypothesis that there was a possible correlation between unit price and BLS date ($p = .005$). However, no relationship was found between quantity ordered and BLS date ($p = .957$). Because the slope of the curve was positive for PLT, ALT, and unit price, it can be concluded that an increase in any of these three variables will lead to increased BLS time, and vice versa. AAC codes D and H (stocked) had an inverse relationship with BLS date. Therefore, any D or H item that is in stock takes less time to ship than an item that is not stocked. The fuzzy method based on the Bayesian Markov blankets proposed in this study has the advantage of acting directly to group the trigger outputs, resulting in the development of a set of priorities for the establishment of trigger output buckets. Although fuzzy logic and Bayesian approaches have been used to facilitate group decision making in many areas (Chuu, 2011; Shin et al., 2011), the present study contributes to the literature because it reports a fuzzy induced Bayesian approach to group decision

Table 17
Count of NSNs by trigger.

Trigger	Trigger description	Count
2	NSNs not purchased recently	6211
6	Long ALT and PLT	6503
7	Insufficient technical data	7990
8	Heavy maintenance/wear NSNs	5002
9a	Items that contain a known forging	132
9b	Items that contain a known casting	89
10a	Pricing anomaly	1264
10b	Items with whole-dollar prices	444
10c	Items with a unit price ending in $0.99	153
10d	Items costing exactly $0.01, $0.05, $0.10, or $0.25	99
10e	Items with no price	1
11	Qualified sources, number of suppliers used to purchase item	3549
16	Surge and sustainment item	4851
19	Fabricate or assemble	2
21	Items coded to General Dynamic Land Systems	465
22	Items coded to Delco	356
23	Open 339 on item	27
24	Shelf-life item	279
26	Class code–circuit cards	56

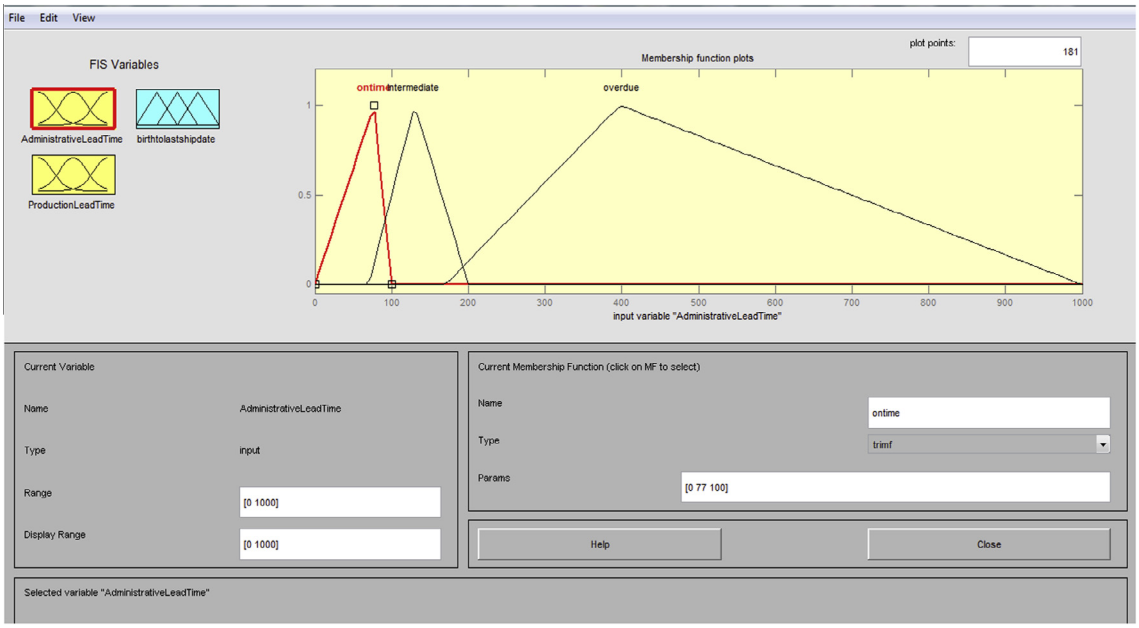

Fig. 10. Administrative lead time.

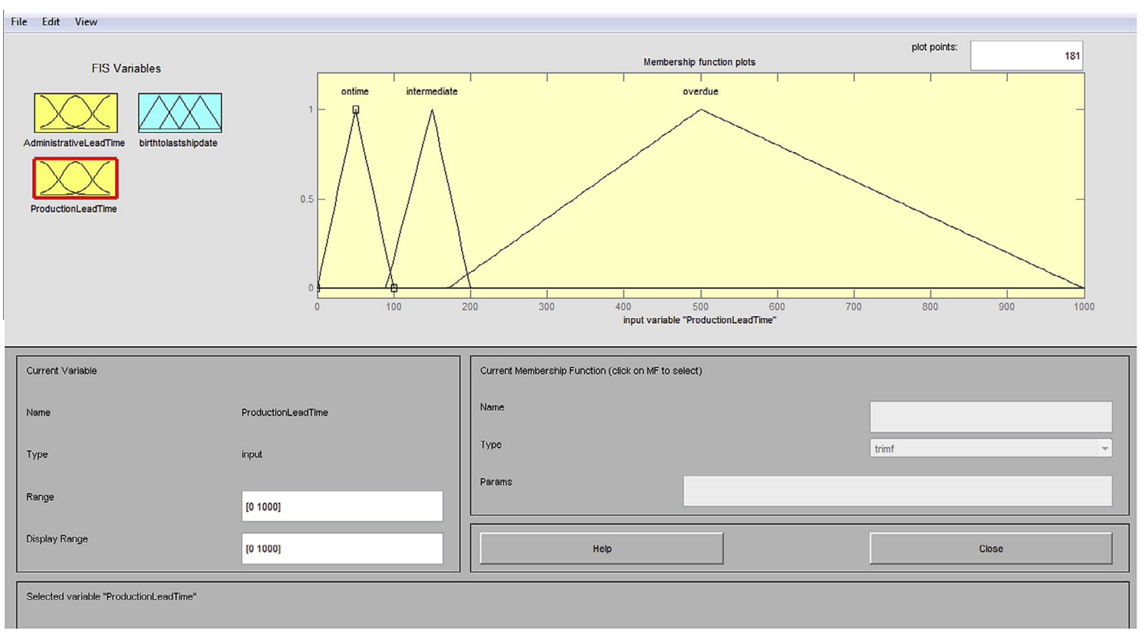

Fig. 11. Production lead time.

making for reducing backorders in the supply chain. The contribution to the literature is enhanced by the use of a real-world example from an aerospace database that presents a hierarchy for evaluating supply chain risk. The proposed method is independent of the membership functions used and is appropriate for use in situations in which assessment information may be qualitative, or precise quantitative information is either unavailable or too costly to compute. However, the method is limited in that it uses approximate reasoning. This fuzzy method of risk evaluation and group decision making in the presence of multiple dimensions and related multiple metrics is very useful for understanding and developing supply chain risk events.

The importance grades or impact ratings must be improved further when evaluating the degree of SCBORT risk triggers, such as high ALT or PLT. If the risk trigger is too high, it may have to be improved. This fuzzy Bayesian assessment scheme should be used to determine the best improvements for SCBORT risk triggers. The model described in this study was based on expert consultation and interactive consensus analysis. Therefore, the evaluation results are more objective and unbiased than those of individual assessments.

6.2. Discussion and limitations

One limitation of this study is the sample size. Although the original set of 11,000 real-world backorders appears to be a fairly large sample size, it only represents a subset of all of the possible combinations of known variables that may be observed in the real

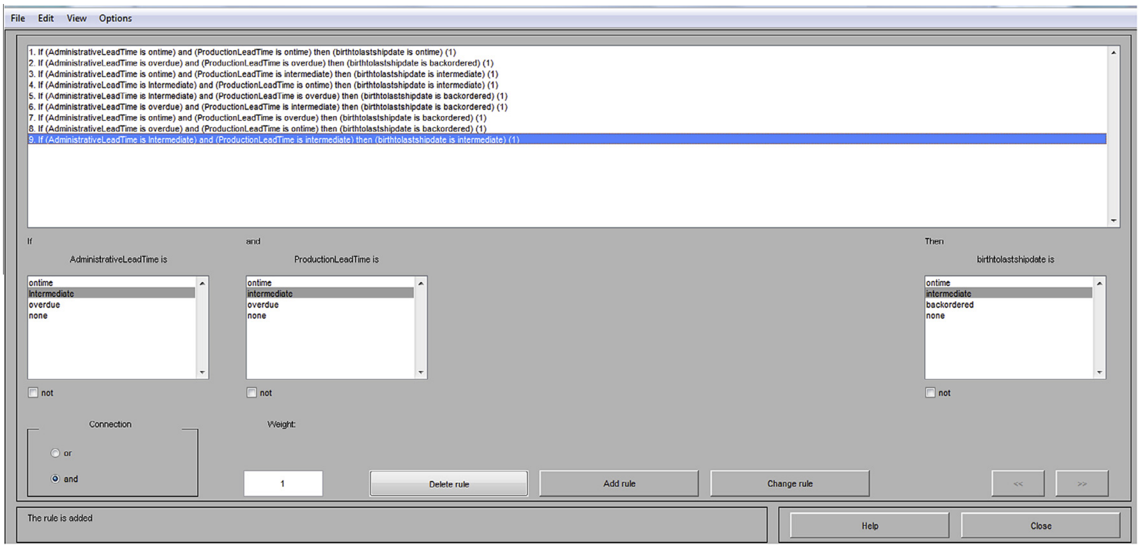

Fig. 12. Nine rules generated.

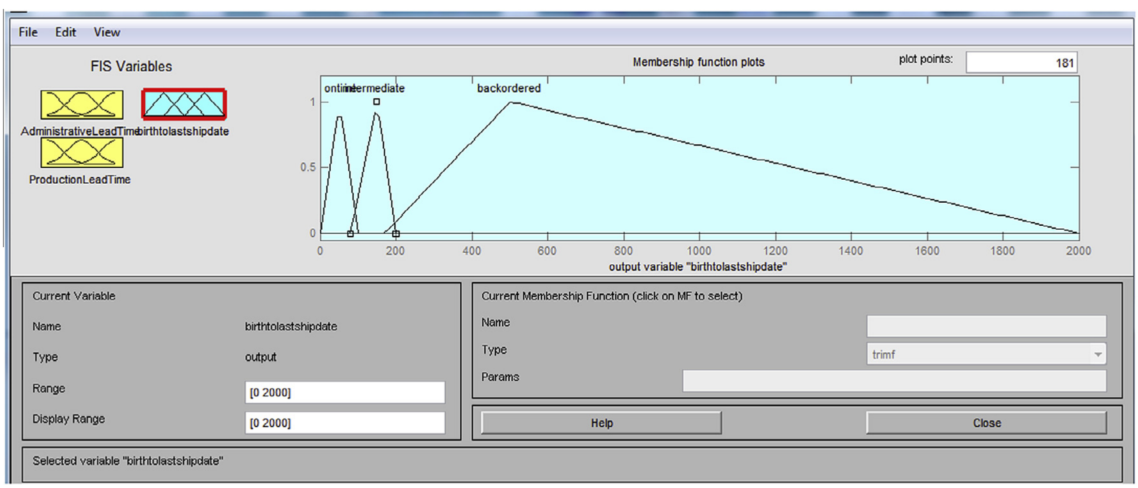

Fig. 13. Birth to last ship date.

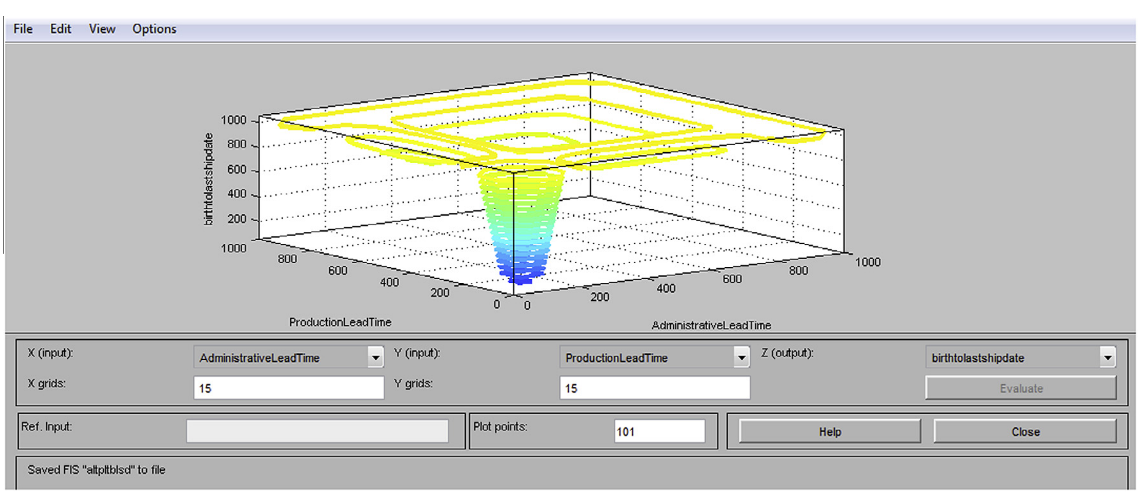

Fig. 14. Funnel diagram to demonstrate the relationship between ALT, PLT, and BLSD.

world. Increasing the sample size to include more real-world projects would result in fewer missing values in the conditional probability tables. As more projects become available in the future, researchers may be able to obtain more complete probability distributions of the BLS date variable. The posterior probabilities generated from our simulation provide some guidelines to help supply chain project managers assess whether the backorders in their projects are typical or unusual. Given that Bayesian networks work well with discrete values, the posterior probability distribution can be incorporated into an IF-THEN expert system that can serve as a cost/schedule overrun detector. We believe that such an expert system may allow supply chain project managers to contain backorder costs.

The concept of backorder as currently used in the defense logistics community is vague and does not differentiate between temporal backorders and B3I war room critical parts. Under the B3I, if the lack of a critically needed part is hindering military operations, the defense logistics community is quickly mobilized to procure, manufacture, and deliver the part. However, many of these parts are not temporally backordered—that is, they do not have long lead times. It is not that the procurement system and industrial base are functioning abnormally; rather, in the judgment of the officers involved in ordering parts identified as B3I parts, the parts are simply critical enough that they require additional expediting and due diligence. Temporal backorders, in contrast, have long ALT and/or PLT.

6.3. Future issues

The value and benefits of this Fuzzy Feasibility Bayesian Probabilistic Estimation decision support tool prototype can be extended to other Department of Defense systems. These future efforts will help to refine and enhance the risk analysis methodology, develop an improved prototype decision support tool, and apply it to other systems that are operating beyond their original service lives. The resulting ability to proactively predict and address problems with parts availability before they occur will help avoid backorders, reduce the costs associated with meeting unexpected shortfalls, and increase supply chain readiness and effectiveness in the planning application domain.

Triggers were chosen for analysis from the various supply items listed by National Stock Number (NSN). The criteria used to determine high risk levels for these items and the groupings of the items were determined following an initial assessment of the triggers. In the future, Pareto Charts, Perti Nets and ISO 31000 process methods may be adapted to evaluate the triggers for parts backorders and to assess future sustainment, risks, and benefits of using new technology to address logistics readiness factors that affect equipment service life. This future analysis may include a review of the data on past maintenance history, stock-on-hand reports, Federal Logistics Information System procurement and technical data, casting and forging data, U.S. Marine Corps 339 lists, and the Warstopper Surge & Sustainment list. Conceivably, this process may result in the creation of a trigger methodology for risk identification and prioritization, problem identification, and further analysis of alternatives to mitigate risk and to recommend a path forward.

We envision two possible future mechanisms for predicting the propensity for backorder among specific NIINs. The first would compare NIINs as they are entered into the requisition system to a known subset of NIINs with a long backorder status. Any NIIN in the ordering process that is already known to have a long backorder status would be flagged to notify buyers and logisticians of the existing backorder status. The second approach would filter NIINs as they are entered into the requisition system, flagging possible long backorder items based on specific attributes previously identified. By comparing the incoming NIIN to a set of known variables and combinations of variables, logisticians or buyers can also identify NIINs with a propensity to become backordered. Based on work to date, we believe that both approaches are technically feasible, as both use data already in DLA's possession. We believe that such an expert system may allow DLA buyers to contain backorder aging and assist in shortening B3I wait times.

As demonstrated here, B3I backorders may be due to behavioral or perceptive factors in addition to the impact of ALT and PLT variables. From a time or temporal technical perspective, we discovered (using regression, cross-tabs, descriptive statistics, and Bayesian techniques) that the data support a relationship between ALT, PLT, and BLS. The results of statistical analysis with nonparametric methods, such as neural networks, Tabu search, genetic algorithms, Bayesian networks, Markov processes, Monte Carlo simulation, ant colony optimization, logit, probit, particle swarm, and expert system applications, might also provide insights into the backorder phenomenon. These algorithms may be incorporated into a Web-based application, such as an expert system, that can aid decision makers in determining the probability of backorder aging for a specific item. In the future, other possible additional independent variables could be investigated. These include, but are not limited to, type of material, tech data availability, last time bought/number of days ratio, proportion of replenishable to non-replenishable items, freight and packaging attributes, and shipping.

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