Research Article

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Bayesian belief network for assessing impact of factors on army's lean–agile replenishment system

Abstract: A dynamic time-separated lean–agile spare part replenishment system can prove beneficial to the army by being efficient (cost saving) during peace and effective (assured availability) during war. The logistics echelons must have certain attributes in order to implement such a dynamic replenishment system. The purpose of this article is to identify the factors/attributes that are necessary in a spare part replenishment system of vehicles and weapon platforms in order to implement a time-separated lean–agile strategy through a systematic literature review. Furthermore, the article will investigate the impact of these factors/attributes, individually and collectively, on overall system performance. This will enable logistics managers to focus only on the factors that have greater impact on the system. A model explaining the effects of various contributory factors/attributes on the overall logistics system has been developed through a comprehensive literature review, experts' judgments and inputs from practising logisticians in the military field. The article then models the system using a Bayesian belief network (BBN) on Netica software. After the development of the model using Netica, a sensitivity analysis based on the mutual information criterion is conducted to identify the critical factors that most significantly affect a dynamic lean–agile spare part replenishment system. The study addresses the identified need of applying BBN to model an uncertain and complex military logistics domain.

Keywords: lean–agile, Bayesian belief network, army, spare part replenishment, logistics, supply chain management

1 Introduction

Military logistics is the "science of planning and carrying out the movement and maintenance of forces", including acquisition of services and [...] (NATO 2007). It aims at achieving operational results rather than economic results. The interest of defence, and, by extension, defence logistics, is [...] "to advance the effectiveness and efficiency of the military", whose duty is to protect and defend the public interest and the long-term security of the State (Yoho et al. 2013). Military logistics in the past have been following the concept of "just in case" stocking of supplies. The transition from peace to war is considered an inevitable event for which governments (and, ultimately, taxpayers) are prepared to set up and maintain large military forces (Kovacs and Tatham 2009). This "massing of large quantities of material [...] provide[s] a buffer against uncertainty", but it has invited a "fierce criticism of the creation of these iron mountains". There is some academic research "that explores the tension between massing too much and becoming too lean" (Yoho et al. 2013). Essig et al. (2010) highlight that the military logisticians are "confronted with the pressure to ensure efficiency while, at the same time, taking into consideration the pressure to ensure operational effectiveness".

The two contradictory requirements from the military logistics chain (to be both lean and agile) can be fulfilled by separating the two in time. The logistics chain can remain lean (cost-efficient) during peace and can move to an agile mode (assured availability through effectiveness) during war. There is an inevitable demand (from military logistics) for improvement in cost-efficiency during the periods when not in action (Tatham 2006). However, the armed forces must transition to a posture in which effectiveness is paramount and cost a secondary consideration when the country goes to war (Kovacs and Tatham 2009). This transition "from an efficient (peacetime) to an effective (wartime) posture (and back again)" also needs to be very quick (Yoho et al. 2013). In effect, we need the military

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logistics chain to work in both the modes (lean and agile) at different times and have the capability to make this switch without delay. The logistics chain needs to have a dynamic time-separated lean–agile supply system. The term lean–agile has been used in this study specifically to emphasize the point that the lean and agile modes are being followed at different times and can actually be considered as two separate supply chains. This is different from the term leagile, which refers to a supply chain that has a decoupling point that separates the lean part from the agile part of the same chain. For this dynamic switch to happen, we need to figure out the attributive factors that can make the replenishment system capable of doing this. There is also a need to prioritize these factors so that those factors that have the most impact can be addressed first, thereby making the replenishment system capable of working in both lean and agile modes at different times.

Bayesian networks (BNs), also called belief networks, Bayesian belief networks (BBNs), Bayes nets, and sometimes also causal probabilistic networks, comprise an increasingly popular method for modelling uncertain and complex domains (Uusitalo 2007). It has been used in diverse applications such as assessment of probabilities of falling down from height at work (Alizadeh et al. 2014), supplier selection (Dogan and Aydin 2011), environmental modelling (Uusitalo et al. 2005; Celio et al. 2014), health applications (Chang et al. 2015), etc. In this study, we use BBNs to construct a model depicting the causal relationships between various attributes of a replenishment system in the Army and, then, conducting a sensitivity analysis to arrive at the most critical of these attributes. The replenishment system being considered is the spare part replenishment system of vehicles and weapon platforms being followed in the Army.

In Section 2, we present a brief literature review of the lean, agile and lean–agile concepts; BBN and its use in modelling real-world situations in logistics and military applications using probabilities and their distributions. This section also brings out the gaps in the research in the field of using BBNs in military logistics. In Section 3, we provide a brief introduction to BBNs and the meaning of mutual information, which is a criterion used to indicate the sensitivity of one variable to the other. In Section 4, we describe our model and illustrate the methodology for constructing it. In Section 5, we discuss the results of the sensitivity analysis of the constructed BBN and identification of critical factors that most significantly affect a dynamic lean–agile spare part replenishment system. The sensitivity analysis is conducted using a mutual information criterion. We also present validation of the model in this section. The results of the section can be used to focus on the critical factors identified by the sensitivity analysis

of the model, thereby easing the implementation of the new replenishment system. The last section is devoted to the discussion and conclusion of the article.

2 Literature review

2.1 Lean, agile and lean–agile supply chain in industry and army

Lean is a concept that works by reducing the *muda* or waste. Ohno (1988) has shown that lean practices can lead to cost savings by elimination of waste. Lean thinking, as introduced by Womack and Jones (1996), has taken the concept of waste elimination from merely manufacturing processes to the whole of business practice. A Lean Supply Chain strategy is one that is aimed at creating a cost-efficient supply chain, with a focus on reducing inventory lead times and waste (Wang et al. 2004). The strategy works well with stable and predictable demand (Fisher 1997; Qi et al. 2009).

The origins of agility as a business concept lie in flexible manufacturing systems. The concept of manufacturing flexibility was extended into the wider business context (Nagel and Dove 1991) and the concept of agility as an organizational orientation was born (Aitken et al. 2002). Just as the lean-thinking concept emerged out of lean manufacturing, agility has been used as an organizational orientation and not as only a manufacturing strategy (Nagel and Dove 1991). Christopher (2000) defines agility as "a business-wide capability that embraces organisational structures, information systems, logistics processes and, in particular, mindsets".

Supply chain strategies can be classified as those that emphasize cost reduction (lean), quick response (agile) or a mix of both. Shewchuk (1998) suggested that one single strategy, be it lean or agile, cannot be equally suitable to all types of supply chains. Fisher (1997) was the first to segregate products based on their characteristics and proposed different supply chain strategies for each type. It was only a matter of time when the industry realized the potential of combining the two strategies. Naylor et al. (1999) demonstrated that the two strategies, lean and agile, are not mutually exclusive. There are several examples that show the need to develop hybrid strategies (Christopher and Towill 2000). It was confirmed by Krishnamurthy and Yauch (2007) that lean and agile can coexist and they illustrated it by using data from a company in the USA. Agarwal et al. (2006) used an analytic network process to integrate the various criteria of decision-making and concluded that

leagile is a better supply chain management (SCM) strategy than lean or agile. Aitken et al. (2005) identified seven discrete pipelines (or seven different supply chains) and illustrated them by using the case study of a lighting company. The separation of the supply chains, however, was based on clustering products into different kinds and thereby taking decisions to manage the supply chain based on the family of products that it catered to. A similar methodology that marries lean and agile has been illustrated by Towill and Christopher (2005), wherein they have segregated the activities in time and in geographical space. The methodology has been explained in the context of the healthcare industry in the UK.

Peltz et al. (2008), in their study, proposed a methodology for achieving leanness by designing wartime distribution networks that exploit the strengths of airlift and surface transportation modes to meet combatant command requirements at the lowest possible total cost. Girardini et al. (2004) introduced a method for determining stock levels at forward locations during wartime to ensure a more agile logistics system. Breunig et al. (2006) highlighted that the military must not only

be agile, flexible, robust and effective, but also lean and efficient. In order to optimize military logistics, the requirements of the military must be balanced with the budget. Yoho et al. (2013) underlined the requirement for further research that explores the tension between massing too much and becoming too lean, as well as understanding how resilience may be achieved at the lowest possible economic cost.

2.2 Logistics applications of BBNs

The BBN has been used to model various logistics problems and derive meaningful decisions. A summary of the literature is presented in Table 1.

2.3 Military applications of BBNs

There has been a wide variety of applications of BBNs in the military field. The summary of the literature on this topic is given in Table 2.

Tab. 1: Logistics applications of BBN.

Literature	Contents
Soberanis and Elizabeth (2010)	Uses an extended BBN approach to analyse supply chain disruptions. The study is aimed at developing strategies that can reduce the adverse effects of disruptions and hence improve overall system reliability.
Li et al. (2006)	Model the supply chain as a BBN that depicts the operations centres, material, and material flow; use the network to ascertain the time and cost of a disruption.
Li and Gao (2010)	Use BBN to solve the collaborative efficiency of enterprises in a supply chain.
Anderson et al. (2004)	Use BBN to model a service–profit chain in the context of transportation service satisfaction. The BBN is used to arrive at probabilistic inferences concerning customer loyalties, service input variables and service recovery.
Sutrisnowati et al. (2015)	Analyse the lateness probability using a BBN by considering various factors in container handling. By this method, one can infer the activities' lateness probabilities and provide recommendations sequentially to port managers for improving existing activities.

Tab. 2: Military applications of BBNs.

Literature	Contents
Johansson and Falkman (2008)	Develop a threat evaluation system in an air defence scenario. The BBN-based approach makes it possible to handle imperfect observations.
Wang et al. (2012) and Hou et al. (2010)	Use a dynamic BBN for Air Defence threat assessment. The advantage of using BBN is that it can modify the threat assessment knowledge repository dynamically, which enables the assessment model to possess better adaptability for producing more accurate assessment results.
Hudson et al. (2001)	Describe a software tool Site Profiler that assists antiterrorism planners at military installations to draw inferences about the risk of terrorist attack.
Jha (2009)	Develops a model to predict the likelihood of future terrorist activities at critical transportation infrastructure facilities.

Tab. 2: (continued)

Literature	Contents
Kruger et al. (2012)	Uses BBN for identification of a tracked object and assessment of its affiliation and threat potential in maritime surveillance.
Xiang et al. (2008)	Develop an intelligent decision support system for military situation assessment. Use BBN models as decision models that have the ability to model and reason under uncertainties. BBN is updated as the situation develops and fresh inputs are available.
Laskey et al. (2000) and Wright et al. (2002)	Develop a model to solve a common dilemma in the minds of military planners to segregate important information from within a large volume of available information from diverse sources during conflicts.
Gillies et al. (2010)	Introduce modelling and analysis techniques for sensor-enabled missions that quantify the uncertainty in the data and provide a means to estimate the quality of information using BBNs.
Falzon (2006)	Describes a centre of gravity (COG) analysis by military commanders. COG is affected by a number of critical capabilities (CCs), with each CC having a number of critical requirements (CRs), which in turn have critical vulnerabilities (CVs) that are targeted through a proper course of action. The authors use causal probabilistic networks to represent the relationships among the CCs and CRs for a COG construct.

2.4 Research gaps

Most of the research into applications of BNs in the military field is limited to tactical situations. Problems related to weapon allotment against aerial threats (Cutler and Nguyen 2003; Oxenham and Cutler 2006; Johansson and Falkman 2008; Hou et al. 2010; Wang et al. 2012), for counterterrorism (Sun et al. 2005; Goldstein 2006; Hudson et al. 2001; Jha 2009), military decision-making (Laskey et al. 2000; Wright et al. 2002; Xiang et al. 2008) and sensor data collection (Gillies et al. 2010) have been addressed using BBN. Logistics application of BBN involves supply chain disruptions, which can be mapped using BNs, and arriving at the probabilities of these disruptions by considering the contributing variables (Anderson et al. 2004; Li et al. 2006; Li and Gao 2010; Soberanis and Elizabeth 2010; Sutrisnowati et al. 2015). BBN as a concept has been widely used and validated in a large number of applications. However, its application in the military logistics field is not widely researched. This study will bridge this gap in literature, particularly in relation to the use of BBN in military logistics.

In the next section, we describe the theory of BNs, including the concept of mutual information in sensitivity analysis.

3 BBN analysis

BBNs are graphical models that are used to model the knowledge domain. They use Bayesian probabilities to model the dependencies within the knowledge domain (Jensen 1996). BBN is a directed acyclic graph that has a structure, as well as parameters that define this structure.

A BBN comprises two parts, qualitative and quantitative. The qualitative part consists of nodes and arcs. These nodes are a graphical representation of the stochastic variables being modelled and the arcs represent the direct causal relationships between these variables. Depending on the structure of the network, the nodes may be parent (or the root node), child (one that has one or more parents) or leaf (one with no child) nodes. These nodes, or the variables, can be either discreet or continuous. The nodes can have a number of states with certain probabilities, which are calculated from the predetermined conditional and prior probabilities. The quantitative part of a BBN is the conditional probability table, which describes the relationship between various variables.

Bayesian networks work on the concept of conditional probabilities, which is mathematically given by the following formula:

$$p(x \mid y) = r \qquad (1)$$

This means that if $Y = y$, and all other factors are fixed for $X = x$, then $p(x) = r$.

Consider the hypothesis H that event $X = x$, given the evidence e that $Y = y$. The probability of the hypothesis H being true given that evidence e has occurred is called the posterior probability of H and is given by the equation

$$p(H \mid e) = \frac{p(e \mid H)p(H)}{p(e)} \qquad (2)$$

where $p(e \mid H)$ is the likelihood of the evidence e occurring if the hypothesis H is true, $p(e)$ is the prior probability of the evidence and $p(H)$ is the prior probability that H is the correct hypothesis without considering the evidence (Darwiche 2009).

A BBN is used to ascertain whether the change in probability of an event affects the probability of other events. The quantified effect of this change can be calculated by knowing the joint probability function of all the variables. Let $X = \{X_1, X_2,..., X_I\}$ be a set of random variables such that X_i is a random variable for each vertex in the graph. For each random variable X_i, there exists a parent set of X_i, denoted $\text{parent}(X_i) = \{Y_1, Y_2,...,Y_n\}$. Using the chain rule, the joint probability density $X = \{x_1, x_2, x_3,..., x_I\}$ can be written as follows:

$$P(x_1, x_2, x_3,..., x_I) = P(x_1x_2, x_3,..., x_I)P(x_2x_3,..., x_I)$$
$$P(x_3x_4,..., x_I)... P(x_I)$$
$$= \prod_{i=1}^{I} P(x_i \,|\, \text{parent}(X_i)) \tag{3}$$

This is nothing but the product of all the conditional probabilities specified in the BBN (Darwiche 2009; Dogan and Aydin 2011; Sutrisnowati et al. 2015). The major benefit of using a BBN is to derive inferences with partial information. The network is flexible enough to recalculate various probabilities if some new evidence becomes available.

Mutual information measures the information that random variables X and Y share. It measures how much knowing one of these variables reduces our uncertainty about the other (Wang et al. 2011). The mutual information of X and Y is given by

$$I(X,Y) = -\sum_{y}\sum_{x} P(x,y) \log \frac{P(x,y)}{P(x)P(y)} \tag{4}$$

where $P(x,y)$ is the joint probability distribution function of X and Y, and $P(x)$ and $P(y)$ are the marginal probability distribution functions of X and Y (Cai et al. 2013).

In the next section, we explain the methodology used to construct our model, followed by the model itself. Validation of the model is performed at the end of the next section.

4 BBN of a spare part replenishment system

The spare part replenishment system in the army needs to be efficient when the army is not fighting a war and be capable of speedily replenishing spare parts in times of war. These distinct capabilities of the spare part replenishment chain can be achieved by changing the decision variables that directly affect the supply chain. When these decision variables take values assigned to them in the lean mode, the supply is efficient, with certain acceptable

unavailability allowed. When these decision variables assume values of the agile mode, the supply becomes quick, with utmost importance given to the reliability of the equipment (Sharma and Kulkarni 2016). However, it is necessary that the spare part replenishment system be capable in itself to assume these two modes, lean and agile. In addition, the system must have the ability to quickly switch between the two modes, especially from lean to agile when the army goes from peace to war. A BBN approach has been used to determine those factors that have the most impact on the capability of the system to be both lean and agile at different times, as well as to quickly move from one mode to the other. This approach has been explained in detail in the following sections.

4.1 Methodology

The research was conducted with the help of an exhaustive literature review to arrive at the factors that have an influence on the ability of the system to be lean or agile and its capability to make the switch. In Step 2, a panel of four experts deliberated, to determine the causal relations between these factors and to assess their relative impact on the system's capability. These experts were selected based on their experience in the field of military logistics. Each of these experts had a minimum of 18 years' experience in this field and was also a postgraduate. This ensured that the expert had knowledge both of the domain as well as of the techniques used in academics. In Step 3, these experts decided on the meaningful states of these factors, with emphasis on maintaining the number of states limited. In Step 4, the various factors or the variables were assigned conditional probabilities. These probabilities were compiled and then sent back to the experts for further iterations. The model was qualitatively validated with additional information from practising managers of military logistics. A total of eight practising managers were selected based on a minimum experience of 10 years in the field. This validation was done by asking relatively simple questions about the differing impacts of each of the factors on the final state of the system. It was ensured that the model is not changed completely but is adapted to the inputs of these practising managers. The methodology is explained in Figure 1.

4.2 Factors

Chase et al. (2009) in their white paper, have listed certain characteristics of industry leaders. According to the

Step 1: Literature Review for Selection of Factors

Step 2: Final selection and establishing causal relations between these factors

Step 3: Modelling of the relationships between the factors on Netica

Step 4: Quantitative validation of the network

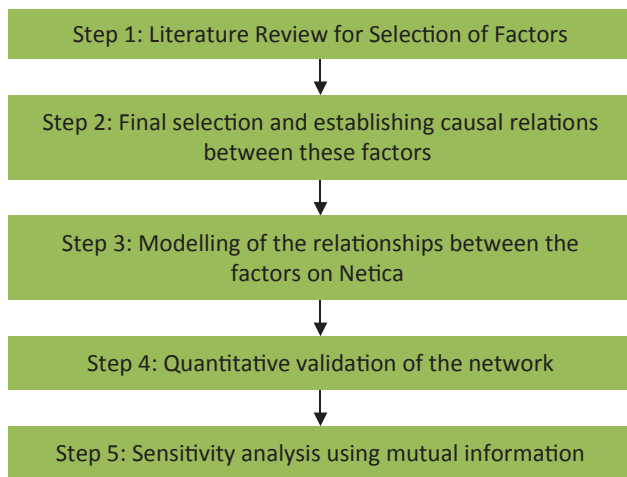Step 5: Sensitivity analysis using mutual information

Fig. 1: Methodology.

authors, leaders are more likely to use demand analytics and reporting (e.g. simulation, what-if analysis and scenario planning tools). Best-in-class organizations consistently shared many characteristics such as the ability to include causal factors (e.g. weather, natural disasters, competitor actions, and so on) into demand forecasts. Furthermore, in that article, they highlighted that forecasters cannot rely exclusively on historical patterns as a good predictor for the future; hence, there is increased focus on effective, real-time access to consumption data for more accurate demand forecasting and planning. Leading companies use integrated collaborative forecasts with customers. Resounding consensus emerged across all industries that "access to timely consumer data and new product forecasting were their biggest challenges to effective demand management". Lockamy and McCormack (2004) emphasize the requirement of advanced SCM practices, such as collaborative forecasting and planning with customers and suppliers. Lee et al. (2000) pointed out that by letting the supplier have visibility of point-of-sales data; the harmful effect of demand distortion can be ameliorated. Chen et al. (2000) indicated that providing each stage of the supply chain with complete access to customer demand information can significantly reduce increase in variability of the orders placed by the retailer.

Use of modern technologies such as radio frequency identification (RFId), bar coding and warehouse management systems (WMSs) has eased the problems associated with warehousing, such as inventory inaccuracies, product misplacement and so on (Sahin 2004). Bar codes, sensors and/or RFId are used for the track-and-trace functionality throughout all supply chain processes (supply, manufacturing and distribution) (Heinrich 2005). RFId, in combination with other systems, is becoming the basis

for new solutions, contributing to better management of supply chains in terms of cost reduction and improvement of customer service levels (Sahin 2004). Benefits of using RFId include the reduction of labour costs, the simplification of business processes and the reduction of inventory inaccuracies (Rekik et al. 2008). The cause for the out-of-stock issue is the factor related to store shelving and replenishment practices, in which the products ordered are in the store but not on the right shelf. These factors may be related to shelf space allocation, shelf-replenishment frequencies, store personnel capacity, in-store execution errors, and so on (Vuyk 2003). The potential benefits of RFId tagging of individual items is huge because the identity, location and authenticity of these items can be easily monitored, thus resulting in increased efficiency and reduced costs (Lee et al. 2005). Inventory record inaccuracy, namely, the discrepancy between the recorded inventory quantity and the actual inventory quantity physically present on the shelf, is a recurring occurrence of, often, considerable proportions (Thiel et al. 2009).

A good distribution-and-inventory control system leads to an efficient system and satisfied customers. Lateral trans-shipment is one such distribution strategy that has a positive impact on a supply chain. Chiou (2008) highlights this as "One strategy in SCM to have an impact on cost, service level, and quality, commonly practiced in multi-location supply chain systems facing stochastic demand, allows movement of stock between locations at the same echelon level or even across different levels". Ross (2002) describes enabling visibility to inventory as a real process value that needs to be achieved. Real-time communication and supply chain visibility are indicators of higher maturity (www.scf.usc.edu). Selective inventory control not only streamlines the inventory but also is helpful in reducing it to a significant level (Bhatia 2008). Meredith (1987) points out that local firms offer better service, are innovative, respond quicker and provide customization and variety. Perry and Sohal (2000) also identify supply from local resources as a good quick response practice. Sheffi (2001) summarizes the solutions to the supply chain problems. The author highlights that the problem can be tackled by focusing on known solutions, i.e. (a) improvement in shipment visibility; (b) improved collaboration between trading partners and across enterprises; and (c) better forecasting through risk-pooling methods. Vendor-managed inventory (VMI) is a tool widely used in industry to cut costs and increase efficiency. Evidence has shown that VMIs can improve supply chain performance by decreasing inventory levels and increasing fill rates (Yao et al. 2007). Achabal et al. (2000) state that

the VMI system reduces inventory costs for the supplier and the buyer and improves customer service in terms of, e.g. reduced order cycle times and higher fill rates.

Human behaviour and organizational culture greatly influence the direction of an organization. Employee involvement schemes have significantly improved operational performance in many businesses (Hanna et al. 2000). Various authors have highlighted the importance of motivation of workforce, technical competence and multi-skilling (Dench 1997; Hopp and Van Oyen 2004; Thakkar et al. 2009). With reference to the workforce, Herzenberg et al. (1998) have pointed that workforce agility may provide a wide range of benefits, such as quality improvement, better customer service, learning curve acceleration, economy of scope and depth. Training activities not only develop employees and improve their skills and abilities but also enhance their satisfaction with the job and their commitment to the organization (Harel and Tzafrir 1999). In addition, human resource management practices such as development-oriented appraisal and comprehensive training show a significant positive relationship with organizational commitment (Paul and Anantharaman 2004).

A summary of the factors is listed in Table 3, along with the references from where they have been drawn. The table also indicates the relevance of each of the factors to each of the modes of the system.

In Step 2 of the research, the selected factors were presented before the panel of experts. The experts, after deliberations, finalized these factors. A total of 23 factors were selected and finalized by the panel of experts. A network highlighting the causal relationship between these factors was also constructed in the step. In Step 3, each of the factors was given possible meaningful states. Various factors, their states and the definitions are given below in Table 4. The table also highlights the factors that have an effect on other factors.

4.3 BBN of a dynamic lean–agile spare part replenishment system

The BBN is constructed using Netica 5.18. It is a commercial software package by Norsys Software Corporation, which can be used to work with BBNs, Decision Nets and Influence Diagrams. The variables finalized in the previous steps and the

Tab. 3: Summary of literature review.

Literature	Factors	Lean	Agile	Capability to switch
Chase et al. (2009)	Demand analytics and reporting	√	√	X
Chase et al. (2009)	Inclusion of causal factors into forecasts	√	√	X
Lockamy and McCormack (2004), Lee et al. (2000), and Chen et al. (2000)	Integrated collaborative forecasts with customers	√	√	X
Chase et al. (2009)	Scientific demand forecasting	√	√	√
Lee et al. (2000)	Visibility of point-of-sales data	√	√	√
Chen et al. (2000)	Customer demand visibility	√	√	√
Achabal et al. (2000) and Yao et al. (2007)	Vendor-managed inventory	√	X	X
Heinrich (2005), Sahin (2004), Rekik et al. (2008) and Lee et al. (2005)	Use of RFId, bar coding, etc.	X	X	√
Sahin (2004), Rekik et al. (2008), and Vuyk (2003)	Correct warehousing	√	√	√
Bollapragada and Morton (1999) and Vuyk (2003)	Fewer random-yield problems	√	X	X
Chiou (2008)	Lateral inventory trans-shipment	√	X	X
Paul and Anantharaman (2004)	Development-oriented appraisals of employees	X	X	√
Paul and Anantharaman (2004) and Harel and Tzafrir (1999)	Comprehensive training	X	X	√
Thakkar et al. (2009) and Dench (1997)	Technical competence of employees	X	X	√
Hopp and Van Oyen (2004) and Herzenberg et al. (1998)	Multi-skilling of workforce	X	X	√
Harel and Tzafrir (1999)	Motivation of employees	X	X	√
Sherehiy et al. (2007)	Mechanistic/organic design of organization	X	√	√
Sun et al. (2008)	Inventory visibility	√	√	√
Bhatia (2008)	Selective inventory control	√	√	X
Hanna et al. (2000)	Employee involvement	X	X	√
Perry and Sohal (2000)	Proximity of suppliers	√	√	X

Tab. 4: Factors affecting a dynamic lean–agile spare part replenishment system.

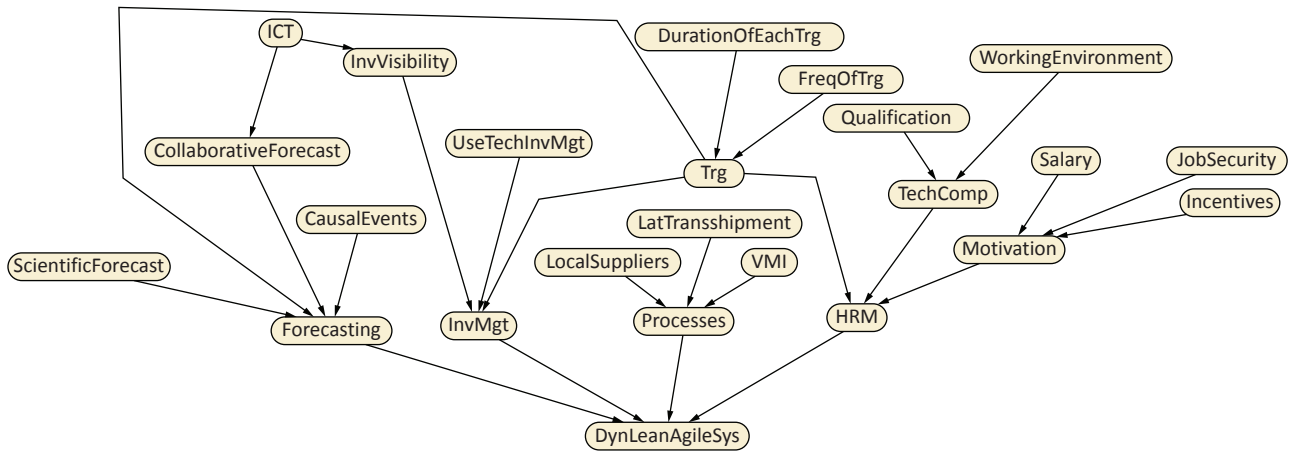| Factor No./Name	States	Influenced by	Definition
F1/Forecasting	[Good, Average, Poor]	Collaborative Forecasting, Scientific Forecasting, Inclusion of Causal Events, Information and Communication Technology, Duration of each training, Frequency of each training	Ability to forecast the requirement of spare parts
F2/Collaborative Forecasting	[Yes, No]	Information and Communication Technology	Use of inputs from all stakeholders for forecasting
F3/Scientific Forecasting	[Yes, No]	N/A	Use of scientific methods to forecast
F4/Inclusion of Causal Events	[Yes, No]	N/A	Inclusion of causal events like training exercise into forecasts
F5/Information and Communication Technology	[Yes, No]	N/A	Presence for ICT for real time flow of information
F6/Inventory Management	[Good, Average, Poor]	Inventory Visibility, Use of Technology in Inventory Management	Use of correct inventory management techniques
F7/Inventory Visibility	[Yes, No]	Information and Communication Technology	Visibility of inventory to all stakeholders
F8/Use of Technology in Inventory Management	[Yes, No]	N/A	Use of modern technologies like RFId, Bar code scanning for warehousing
F9/Processes	[Good, Average, Poor]	Use of local suppliers, Vendor Managed Inventory, Lateral Trans-shipment, Human Resource Management	Use of industry best practices in supply management
F10/Use of local suppliers	[Yes, No]	N/A	Local suppliers for supply of spares
F11/Vendor Managed Inventory	[Yes, No]	N/A	Use of competitive advantage of using VMI
F12/Lateral Trans-shipment	[Yes, No]	N/A	Ability of parallel shifting of spare parts
F13/Human Resource Management	[Good, Average, Poor]	Motivation, Technical competence of Workforce, Training, Duration of each training, Frequency of each training, Qualification, Working Environment, Salary, Job Security, Incentives	Status of human resource
F14/Motivation	[High, Mid, Low]	Salary, Job Security, Incentives	Level of motivation of the workforce
F15/Technical competence of Workforce	[High, Mid, Low]	Qualification, Working Environment	Ability of the workforce to stay technologically aware
F16/Training	[High, Mid, Low]	Duration of each training, Frequency of each training	Level of expertise of the workforce
F17/Duration of each training	[Short, Mid, Long]	N/A	Time period of each of the training capsule
F18/Frequency of each training	[Frequent, Rare]	N/A	Frequency of training for each of the worker
F19/Qualification	[High, Low]	N/A	Technical qualification of the workforce
F20/Working Environment	[Tech, Non Tech]	N/A	Presence of conducive technical learning environment at the workplace
F21/Salary	[High, Mid, Low]	N/A	Monetary remuneration to the workforce as compared to equivalent industry
F22/Job Security	[Yes, No]	N/A	Permanency of the job
F23/Incentives	[Yes, No]	N/A	Recognitions, Bonuses etc to reward better workers

Fig. 2: Bayesian network.

causal relations between them are used to draw the network using the software. Various nodes are then connected with the arcs. Conditional probabilities are filled into the tables. The network can then be compiled to give out reports. Figure 2 is a snapshot of the BBN drawn in Netica 5.18.

4.4 Quantitative validation of the model

Jones et al. (2010) proposed a three-axiom-based partial validation method for BNs. First, a change in the prior subjective probabilities of each parent node should result in a relative change in the posterior probabilities of the child nodes. Second, a change in the value of the parent node should have a consistent magnitude effect on the child node; and third, if both x and y have an influence on the child node, the magnitude of influence of $x + y$ should always be greater than the influence of x and y separately (Cai et al. 2013). In our model, e.g. a change in the parent nodes "incentive", "salary" and "job security" has a corresponding effect on the child node "motivation". The magnitude of change also is consistent. When the "high" state of parent node "salary" is changed from 33.3% to 43.3%, the high state of child node motivation changes from 49.2% to 54.5%. Similarly, a move of high state of parent node salary down to 23.3% moves the high state of motivation down to 43.8%. Furthermore, the combined action of changing the values of the parent nodes incentive, salary and job security has a larger effect on the child node motivation than the effect produced if they are changed separately. The three axioms were checked on each of the nodes and were proved correct, thereby providing partial validation to the model. Combined quantitative and qualitative validation of the model provides the requisite credibility to use the results of the exercise for future research.

5 Results

Mutual information is an indicator used to identify the variable that reveals the most information on a target node and, hence, possible minimum and maximum beliefs can be identified (Kjaerulff and Madsen 2008). The variables that have the maximum impact on the target node can then be selected for improvement. This analysis has been conducted using the "sensitivity to findings" tab in the Netica software menu. Figure 3 is a graphical representation of the analysis. It can be seen that "forecasting" (value of mutual information=8.84%) and "inventory management" (value of mutual information=4.7%) have the most impact on a dynamic lean−agile spare part replenishment system. Forecasting is greatly influenced by the presence of a sound "scientific forecasting" system and "collaborative forecasting". It is also important to point out that the presence of "information and communication technology (ICT)" (value of mutual information=1.02%) has substantial influence on the target node in spite of it being a root node in the fourth tier. This is because it not only affects collaborative forecasting but also "inventory visibility". Inventory visibility has major influence on inventory management, which in itself has considerable influence on the target node. Other variables that have larger impact on the target node are "training" and "use of VMI". Training (value of mutual information=2.09%) is influential because of its simultaneous impact on forecasting, inventory management and "human resource management".

6 Discussion

In order to bring about big changes in an organization, it is necessary that key result areas are identified. These
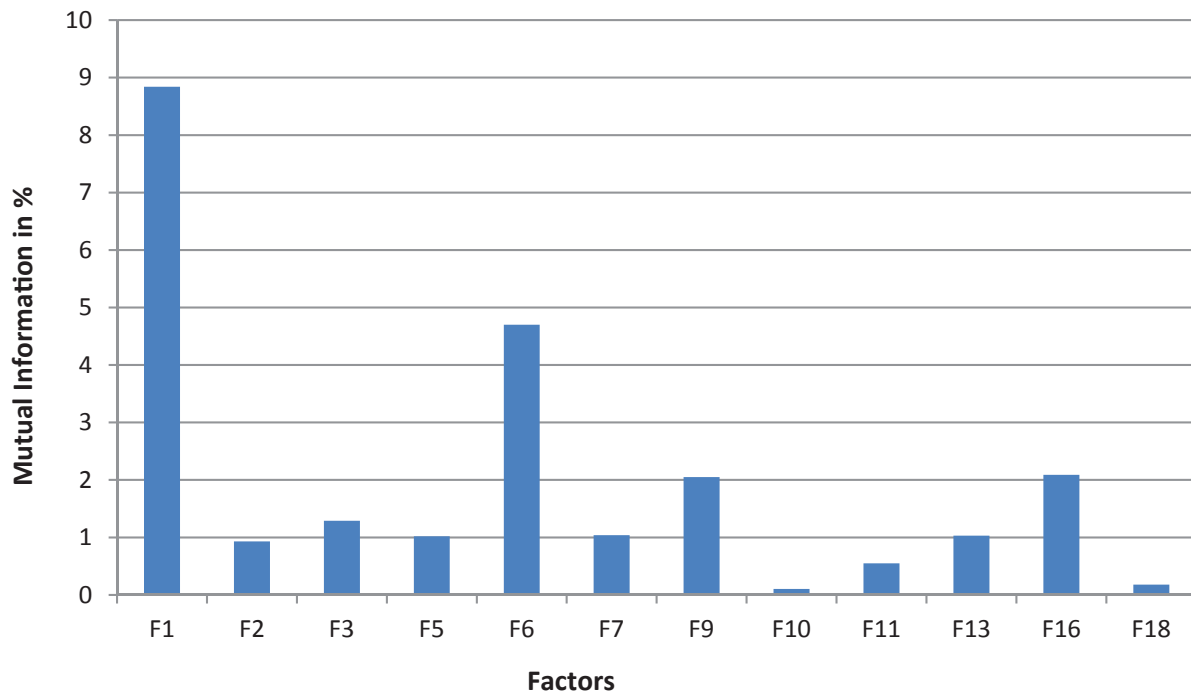
Fig. 3: Mutual information of factors affecting a dynamic lean–agile system (refer Table 4 for details of the factors).

key result areas are influenced by some factors and, therefore, it becomes essential that these factors are identified and special focus given to them to achieve positive results. However, organizations often suffer from inadequate or incorrect data. There is a need for a technique through which these essential factors can be segregated. A BBN of the variables that drive a dynamic lean–agile spare part replenishment system in the Army is such a useful learning tool to distinguish more influential factors from the less influential ones in case of incomplete or imperfect data. It provides a quantified method to highlight factors that have maximum impact on the system, thereby providing a road map to focus on the most rewarding factors. The results of this study indicate that Forecasting has a stronger bearing on the system than other factors. Subsidiary factors such as Inventory visibility and ICT also have considerable impact on the system behaviour. These two factors have overcome the disadvantage of hierarchy (they are considerably away from the target node) and have been able to prove their impact on the target node with the help of sensitivity analysis. This is proof that sensitivity analysis can divulge more information than the network structure. It is, however, necessary to first validate the model, both qualitatively and quantitatively. This validation will provide more credence to the model.

The proposed BBN model has many benefits that enable us to apply it to our case discussed in the study.

The BBN model works well even in the absence of complete factual information and is particularly helpful in "drawing conclusions" (Dogan and Aydin 2011). Any future knowledge can be updated into the model at a later stage and make the findings even more accurate. To begin with, the prior nodes are given uniform probability of occurring, which gives a certain result that is not very accurate. However, fresh inputs, as and when they become available, drive the result more towards accuracy. During qualitative validation of the model, explicit information from the practising managers was updated to further refine the model, which was till then based on parameterization by the experts. This added focused information into the model and aligned it a little more with the ground reality. The practising managers were, in essence, working on the model provided by the experts, who had laid down logically correct boundary conditions, thereby ensuring that any incorrect information from the practising managers is not able to drastically alter the model.

7 Conclusion

Modelling the spare part supply chain on a BBN and the ensuing sensitivity analysis of the factors reveals the key factors that affect the replenishment system. The BBN structure gives a rough estimation of the factors that are

critical; however, sensitivity analysis using the mutual information criterion reveals the hidden influence of certain factors that may seem irrelevant or too far in hierarchy from the target node. From the study, it emerges that accurate forecasting and real-time communication among all the stakeholders has a relatively higher impact than other factors in producing a scheme that is adaptable to a dynamically changing time-separated lean–agile replenishment system of spare parts in the Army. The concept of VMI is another factor that has a considerable impact on the leanness of the system. The model, however, needs to be further refined through the input of more data as they become available. In other circumstances, there may even be some inclusion/deletion/modification of certain factors/relationships. Future work is required to bring out a tailor-made forecasting methodology for the spare parts of the Army, which accommodates all three situations separately, i.e. peace, training exercise and war. Work is also required to lay out a framework incorporating vendor's logistics into the military logistics in a seamless manner, while at the same time ensuring security of information.

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