Expert Systems with Applications 42 (2015) 6539–6551

Contents lists available at ScienceDirect

Expert Systems with Applications

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

Assessment of lean manufacturing effect on business performance using Bayesian Belief Networks

Gülçin Büyüközkan [a,*], Gülgün Kayakutlu [b], İbrahim S. Karakadılar [c]

[a] Industrial Engineering Department, Galatasaray University, 34357 Ortakoy, Istanbul, Turkey
[b] Industrial Engineering Department, Istanbul Technical University, 34357 Macka, Istanbul, Turkey
[c] International Trade and Logistics Department, Nisantasi University, 34030 Sisli, Istanbul, Turkey

ARTICLE INFO

Article history:
Available online 28 April 2015

Keywords:
Lean manufacturing
Bayesian Belief Networks
Scenario analysis
Business performance

ABSTRACT

The challenge of agility for adopting new business norms creates the need for measuring performance under changing conditions. This study aims to demonstrate the financial and non-financial consequences of implementing different combinations of lean techniques on the business performance. Bayesian Belief Network is used in studying the effects of factors under changing conditions. There are seven lean factors and four achievements studied to analyze the impact on three performance indicators. Bayesian Belief Network is constructed on the lean aspects that stimuli flexibility, reliability, quality and time of operations, which will have positive impacts on the financial, non-financial and sustainability performances of suppliers. A case study is carried out for suppliers in the automotive industry and scenarios with different combinations of lean factors are studied. This study gives a new vision in applying Bayesian network for business performance measures considering both the tangible and intangible results under changing business conditions.

1. Introduction

With the publication of *The Machine that Changed the World: The Story of Lean Production* (Womack, Jones, & Roos 1990), the benefits of lean principles have been widely recognized. The term 'lean' implies a series of activities or solutions to eliminate waste, reduce non-value added operations, improve value added processes and maximize performance (Womack & Jones, 1996). Lean principles emphasize system-level optimization, where the emphasis is on integration and how the parts work together as a whole, rather than on individual performance and excellence of any one feature or element (Oliver, Schab, & Holweg, 2007). Originally derived from manufacturing operations, these principles have subsequently also been applied to service operations (Cuatrecasas, 2004; Vlachos & Bogdanovic, 2013; Womack, 2004). Although lean management is widely regarded as a business strategy and implementation of lean techniques improves business competitiveness and organizational performance, few researchers have concentrated on the validation of its positive link with business performance (Detty & Yingling, 2000; Li, Sawhne, & Wilck, 2013; Macedo & Camarinha-Matos, 2013; Singh, Kumar, Choudhury, & Tiwari, 2006; Vinodh & Joy, 2012).

Scenario analysis provides valuable insight with a systematic approach to anticipate alternative future outcomes. This approach facilitates business decisions by taking a number of possible upcoming events in business environments into account and how the performance changes accordingly. As Wong and Wong (2007) states, scenario analysis has high benefits for the decision makers who can estimate the best cut-off points under the previously defined objectives and constraints. Majority of scenario analyses on business performance are focused on the preparation of simulation models for current status continuing without any change, facing the best options to the benefit of the firm or facing the worst conditions (Antón, McCracken, & Potts, 1994; Suryani, Chou, Hartono, & Chen, 2010; Tan & Takakuwa, 2007). Sensitivity analysis can also be performed by changing the input values and multivariable hypothesis testing (Allwood, Laursen, Russell, Malvido de Rodríguez, & Bocken, 2008; Brinckmann, Grichnik, & Kapsa, 2010; Rubio & Corominas, 2008). As a future studies technique, scenario analysis using naïve Bayes is mainly used in success, failure or risk analyses (Groth & Muntermann, 2011; Sun & Shenoy, 2007).

Landuyt et al. (2013) gives a review of Bayesian Belief Networks and states that it has an important role in scenario analysis. This tool has recently taken over an important role of linking quantitative methods with qualitative methods in managerial decision

* Corresponding author.
E-mail addresses: gulcin.buyukozkan@gmail.com (G. Büyüközkan), kayakutlu@itu.edu.tr (G. Kayakutlu), ibrahimsarper.karakadilar@nisantasi.edu.tr (İ.S. Karakadılar).

http://dx.doi.org/10.1016/j.eswa.2015.04.016
0957-4174/

making (Fabian, Cristhian, Ricardo, Diego, et al., 2010; Hänninen, Valdez Banda, & Kujala, 2014; Lee, Song, & Cho, 2010; Li et al., 2013; Shen, 2008; Ulengin, Kabak, Onsel, et al., 2010; Ulengin, Onsel, Topcu, Aktas, & Kabak, 2007). This tool has been widely accepted in constructing future plans by changing the decision parameters, since it performs well in combining the observations and the expert opinions under uncertainties (Cinar & Kayakutlu, 2010; Cinicioglu, Sahin, & Ülengin, 2012; Marcot, 2012; Santos, Santos, Wilkinson, et al., 2011; Dias, 2013; Medina, Jankovic, Okudan Kremer, & Yannou, 2013; Perkusich, Soares, Almeida, & Perkusich, 2015; Zhang, Wu, Ding, Skibniewski, & Yan, 2013).

Lean production has mainly focused on financial savings and reductions in processing time and effort, which are hardcore optimization objectives. Information and knowledge dimensions are the only qualitative and human judgment based variables that are given more attention. Dependency among variables and ambiguity can be resolved by using scenarios for changing the environmental state. There is yet only limited number of studies using Bayesian Network analysis on lean manufacturing implementations by Li, Rajpal, Sawhney, and Li (2009), Li et al. (2013) and Hristea and Colhon (2012). Li et al. (2009) use Bayesian network to improve sustainability using lean techniques. Hristea and Colhon (2012) use Bayes Network to cluster the knowledge for achieving lean business. Li et al. (2013) analyze the risks and supportive processes for the success of Lean 6 Sigma application. These papers emphasize the benefits of Bayes networks in uncertain environments with limited knowledge.

This study aims to determine the effects of lean manufacturing techniques on quantitative and qualitative business performance for manufacturing companies, where several applications are combined. The case study is performed for the Turkish automotive suppliers. There are three objectives of this study; the first is to evaluate the combined performance of qualitative and quantitative lean factors, the second is to resolve the dependence problem faced in linguistic evaluation and the last one is to validate the effect of combined Lean Techniques on financial performance, non-financial performance and sustainability under changing conditions by using Bayesian Belief Network.

The study follows the main steps below:

- *Selecting the Lean factors to be analyzed;*
- *Combining and eliminating independent criteria;*
- *Construction of the cause and effect diagrams among the criteria;*
- *Formation of the Bayesian Map;*
- *Preparing the dependency matrices;*
- *Constructing the Scenarios and perform scenario analysis;*
- *Discussion of the Lean Factor effects on the business performance in different scenarios.*

Following the above workflow, the next section of the article is reserved for the literature review about the impact of lean approach on business performance and scenario analysis studies. The Bayesian Belief Networks are detailed in the third section and the implementation is explained in the fourth section, including scenarios and discussions. Conclusions and suggestions for future studies will be briefed in the fifth and last part. This paper gives a new approach for measuring business performances with a focus in the automotive industry.

2. Literature survey

2.1. Lean effect on business performance

Lean management principles serve the purpose of delivering the highest quality at the lowest total cost, in the shortest time to the customers as well as continuously improving them to achieve perfection for long term benefits (Ramesh & Kodali, 2012). Although the lean concept is a popular manufacturing and managerial philosophy utilized across the globe, successful implementation of lean management can be considered as a complex task, depending on the fact that investments are required to implement this approach. Lean practices can be evaluated as noteworthy, based on the significant returns they generate via operational effectiveness and cost savings (Mackelprang & Nair, 2010). Previous empirical research exposed significant evidences related to lean practices and business performance. In this section, the role of contingency factors is investigated based on the past research findings.

Organizations carry responsibilities to their shareholders with a profit maximization objective. Business performance can be described as a performance criterion, commonly used for capturing the long term behavior of the firm (Olhager & Prajago, 2012). Business performance elements are basically conceptualized as operational-competitive performance (Camacho-Miñano, Moyano-Fuentes, & Sacristán-Díaz, 2012; Mackelprang & Nair, 2010), market performance and financial performance (Olhager & Prajago, 2012; Yang, Hong, & Modi, 2011). Typically; cost, inventory, cycle-time, delivery, flexibility, quality (for operational performance); sales growth and market share (for market performance); return on investments-assets-sales (ROI-ROA-ROS), profits and market value (for financial performance) and other similar measures are used to define business performance.

On the other hand, the lean approach basically tries to eliminate all activities that do not provide added value. Thus, lean practices can reduce costs and improve productivity. Particularly, internal lean implementations might provide higher company profitability due to the performance effect on total cycle-time reductions, better customer service levels and higher profit margins (Camacho-Miñano et al., 2012).

Implementation of lean manufacturing & management techniques improves business competitiveness and organizational performance, owing to the fact that it reduces both the number of defects and the cost of production. Vinodh and Joy (2012) argue that the lean approach streamlines the production process and reduces waste, contributing to the financial performance of the firm. Thus, financial performance should be seen as the ultimate measure of business performance and firm's strategic success (Camacho-Miñano et al., 2012).

Internal lean practices enhance manufacturing and management productivity by reducing setup times and work in process inventory, through which firms can improve their market performance. External lean practices are useful for providing support to solve some innovative problems in the business process, such as new product development, order fulfilment and customer services. Consequently, customer satisfaction can be achieved through increased customer responsiveness and reduced customer lead-time (Yang et al., 2011).

Lower inventory levels, higher quality and operational performance with less waste can be listed among the benefits of lean production (Hofer, Eroglu, & Hofer, 2012). Lean manufacturing & management practices (Amin & Karim 2013; Saurin, Marodin, & Ribeiro, 2011; Arnas et al., 2013) such as, Just-in-Time (JIT), Total Quality Management (TQM), Total Preventative Maintenance (TPM), Pull-Kanban System, Setup Time, Cellular Manufacturing (Layout), Small Lot Size, Housekeeping (5S), Standardized Work, Production Scheduling, Work Groups and Value Stream Mapping are positively correlated with competitive operational performance criteria (Ramesh & Kodali, 2012) like efficiency, responsiveness, productivity and quality. However, all these improvements on competitive priorities also allow the firm to achieve lower cost performance (Arnas et al., 2013).

Even though there is strong relational evidence between lean techniques implementation and business performance, it should not be ignored that in different environmental conditions results might be different due to the effect of contextual factors. Demand variability and product customization level distort implementing some lean practices in the specific market conditions. For instance, in a market condition where demand variability and product customization level are high, inventory level and frequency of delivery might increase, causing negative impact on business performance (Bortolotti, Danese, & Romano 2013). Similarly, other contextual factors such as; industry factors (i.e. average inventory holding level of industry), firm level factors (i.e. size and location differences), production system (i.e. make-to-order, make-to-stock) and product characteristics can also affect the success of lean practices on business performance (Camacho-Miñano et al., 2012; Mackelprang & Nair, 2010). For instance, firms with inventory levels below industry average tend to exhibit greater financial performance (Hofer et al., 2012).

Yang et al. (2011) investigated the impact of regional differences and firm size on lean manufacturing and market performance. They found noticeable differences between small and medium-large sized firms, and European and non-European countries in terms of the strengths of relationship between lean manufacturing and market performance. Large-medium sized firms, as well as firms from Europe show bigger and statistically significant impact of lean practices on financial performance. Kull et al.(2014) investigates the culture effect on the success of lean applications.

According to Olhager and Prajago (2012), lean practices implementation level differs among firms that adopt the make-to-order (MTO) and make-to-stock (MTS) production systems. Lean approach is more applicable for MTS operations, whereas logistics integration is one of the important key success factors for MTO operations. Accordingly, stable demand and supply rates are important for MTS plants, because reducing product variety and working with standard components are critical factors for showing significant impacts on business performance. Li et al. (2013) studies the Lean six sigma factors to improve the manufacturing processes using Bayesian Network approach.

From 2014 onwards Bayesian Network analysis is used more often in performance analysis. Rodger (2014) gives a backorder aging analysis in supply chain management. Rosario et al. (2015) have analyzed the process performance through tacit knowledge using Bayesian networks.

Consequently, based on the contingency theory concept, lean principles implementation should consider financial-market indicators (i.e. ROI, profits, market value, sales growth, market share) and operational performance indicators (i.e. efficiency, responsiveness, productivity, quality) jointly, not ignoring the fact that financial performance is significantly affected by the firm's contextual factors.

2.2. Scenario analysis using Bayesian networks

Harries (2003) defines scenario planning as strategic decisions tested for robustness against possible/plausible future state of actions. Robustness emphasizes the importance of the probabilistic approach in a business world under uncertainties.

A recent article by Stewart, French, and Rios (2013) analyzes the scenario technique as a decision tool to tell stories about the future, explore uncertainty, advocate opposing policies, and define representative samples of future states. Bañuls and Turoff (2011) emphasize the scenario construction; their work indicates the importance of the collaborative Delphi method but proposes the cross impact analysis approach when significant records exist. Dennis, King, and Hind (2000) emphasizes simulation in parallel with the value stream analysis to find where to apply lean factors to improve plans in resource usage. Future scenarios are created for matching available resources and needs. Sharad, Siddharth, and Dipak (2008) uses Pareto Analysis combined with a heuristic model in customer lifetime measurement, creating alternative future revenues from the analyzed customers.

Probabilistic scenarios are recently preferred mainly when analyzing uncertainties. Fuzzy logic (Vinodh & Aravindraj, 2013) and stochastic approaches (Pengfei & George, 2013) have increased the confidence in future suggestions. Aguilera et al. (2013) and Dong, Cheng, Bao, and Yang (2010) are recent examples of wide usage of Bayesian Network based Scenario analysis in the environmental research.

Bayes networks have been accepted as a decision analysis and scenario tool in systematic reviews like in Chai, Liu, and Ngai (2013). Since this method is considered as an artificial intelligence tool, it is mostly used in data mining as in Hristea and Colhon (2012) or in risk calculations as in Hager and Andersen (2010) and Falcon and Abielmona (2012). Li et al. (2009) is one of the pioneers who use Bayesian networks for the business performance, measuring the lean effects on sustainability. Cinicioglu et al. (2012) carries out business performance analysis with scenarios, where the competitiveness in automobile industry is measured and future policies are suggested.

Lean manufacturing performance is generally measured by policies based on the Economic Order Quantity as in Rubio and Corominas (2008) where optimal policies in lean environment are defined. Meade, Kumar, and White (2010) uses ANOVA for suggesting strategies on profitability for discrete events. A fuzzy-logic decision support software is implemented by Achanga, Shehab, Rajkumar, and Nelder (2012) that measures the lean readiness of small and medium size companies and calculates the level of value that will be added by the lean tool used. Hosseini, Aliheidari, and Khademi (2012) implements artificial neural networks trained by using analytical hierarchical process to measure the success of

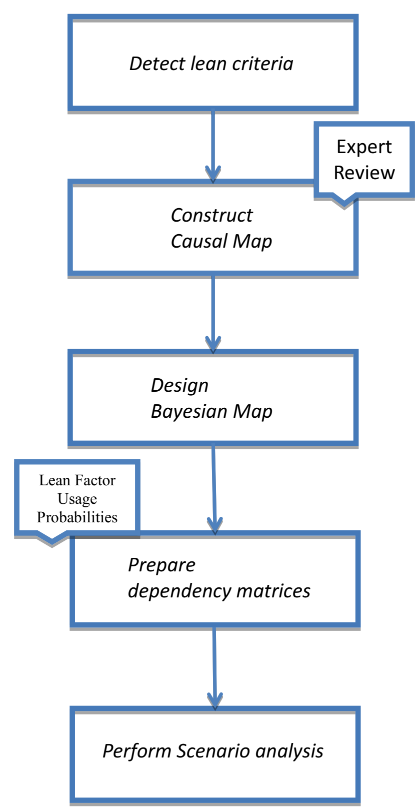

Fig. 1. Implementation Flow.

using lean tools in manufacturing. Li et al. (2013) applies Bayesian Network to prioritize the barriers and supporters on Lean 6 Sigma implementation.

Bayesian Belief Networks are used for the sensitivity analysis in knowledge assessment applications to show the expert judgement on changes of parameters, as expressed by Blackmond (1995), Borth (2002), Danks (2002), Das and Lawless D. (2002), and Ozekici and Soyer (2003). Jiang and Chen (2004) use Bayesian based scenarios in the identification of critical risk factors. The first time when Bayesian Network scenarios are used in stock prediction was realized for fish stocks by Hammond (2004), which opens the doors for using the method in decision analysis and support. Pollino and White (2005) utilize Bayesian network for risk assessment. These authors claim Bayesian Network scenarios are particularly useful for uncertainty analysis for its ability "to consider inadequate knowledge or understanding of system processes, inherent randomness, subjective judgment and vagueness in parameter estimation, disagreement, measurement". Hamilton, Alston, and Chiffings (2005) consider Bayesian Network Scenarios as a data analysis tool as well as a reliable approach for the prediction of future activities in complex problems of environmental sciences. In data mining field Bayesian network scenarios are used in behavioral analysis in social capital performance (Daniel, McCalla, & Schwier, 2007) or agent performance (Lei, Pijanowski, Alexandridis, et al., 2005). Trucco, Cagno, Grande, et al. (2006) use Bayesian Network based scenarios to determine the organizational factors that are influential on risks. Chuanzhe and Fengping (2006) give a review of risk analysis tools where Bayesian Network scenarios are given a special importance because of uncertainty handling. Future scenarios are built by using Bayesian Networks in the customer analytics (Dienst et al., 2010) or in process analytics (Pradhan, Singh, & Kachru, 2007).

Bayesian Belief Networks are preferred to other intelligence methods in complex problems with inadequate knowledge and uncertainties. The use of Bayesian Belief Networks for constructing scenarios in decision support is widely accepted by almost all industries like transportation (Ulengin et al., 2007), foreign investments (Adusei-Poku, Van den Brink, & Zucchini, 2007), logistics (Nanjing, 2008), human–machine interaction (Gregoriades & Sutcliffe, 2008), technology roadmap (Lee et al., 2010) and energy (Cinar & Kayakutlu, 2010). This tool is also used for problem structuring as in Ulengin et al. (2010) and in efficiency measures as in Fabian et al. (2010).

More than hundred researches used the Bayesian Network based scenario analysis since 2010 for different objectives like financial loss assessment (Hager & Andersen, 2010), cultural analysis (Santos et al., 2011), stock market analysis (Khorram, Ping, & Hui, 2011), customer churn analysis (Kisioglu & Topcu, 2011), competitive analysis (Cinicioglu et al., 2012) and project lifetime analysis (Dinwoodie, McMillan, Revie et al., 2013). Industrial applications of performance prediction (Marcot, 2012) and cost effectiveness analysis (Dias, 2013) are also worth mentioning.

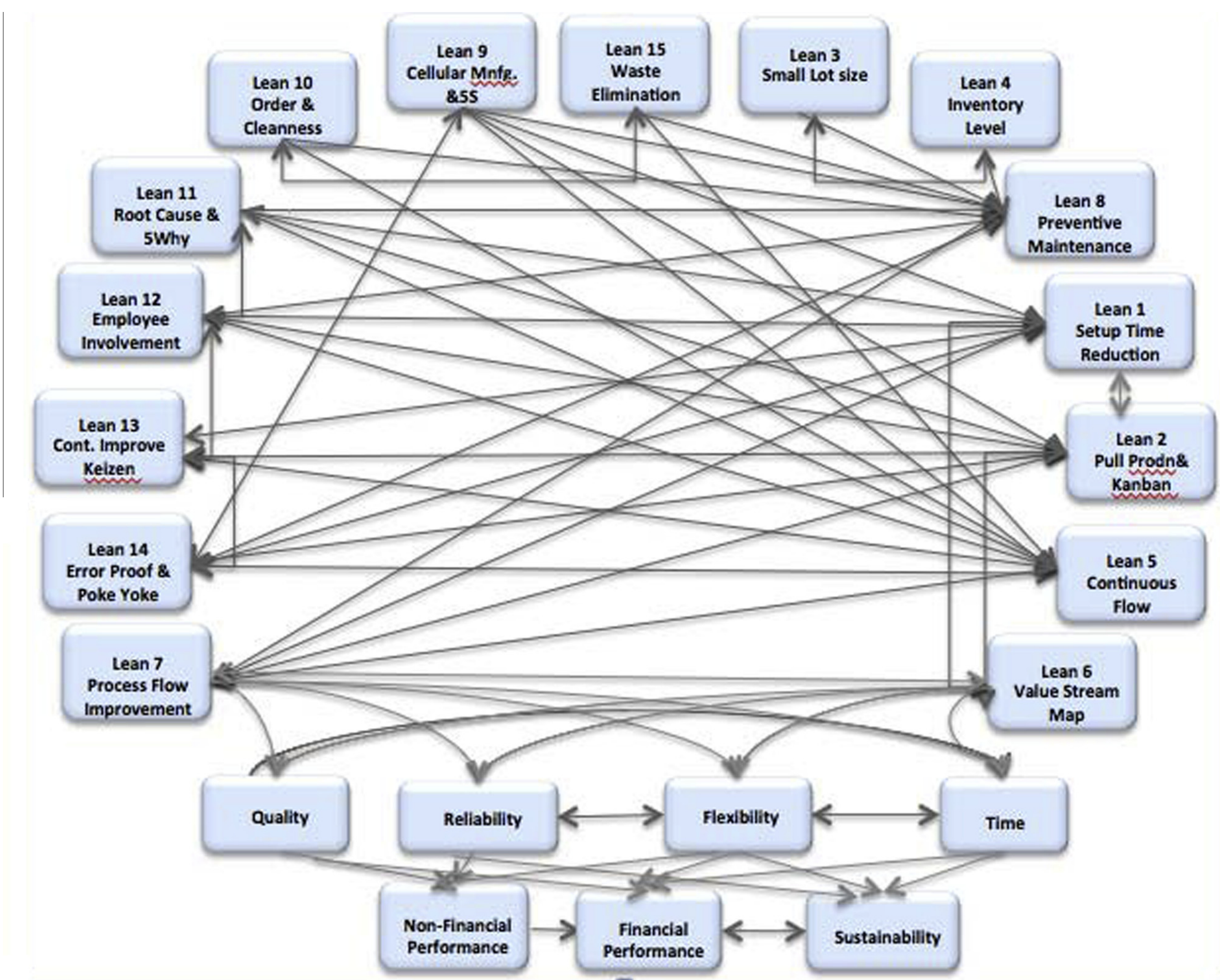

Fig. 2. Causal Map.

Sarkis and Dhavale (2015) select suppliers using Bayesian Belief Networks.

3. Methodology: Bayesian Belief Networks

In complex systems caused by the integrated analytics of the qualitative and quantitative attributes, it is rare to find deterministic relations. A probabilistic approach is required to capture the uncertainty among the basic elements of a model. One of the common probabilistic graphical models specialized in representing and reasoning with uncertain knowledge and/or incomplete data sets is Bayesian networks, also known as belief networks. They combine principles from graph theory, probability theory, computer science, and statistics (Ben-Gal, 2007). Both Heckerman (2008) and Jones, Jenkinson, Yang, and Wang (2010) summarize the advantages of using Bayesian as predicting consequences of interventions and dynamism in renewing the model with modified information in addition to the mathematical and graphical representation of conditional dependencies.

Bayesian networks are directed acyclic graphs, where nodes represent random variables of interest and edges represent informational or causal dependencies among the variables (Celeux, Corset, Lannoy, & Ricard, 2006). The nodes are defined as the parent and the child according to the direction of arrows; the source of the arrow is the parent and the directing node is the child (Cinar & Kayakutlu, 2010). The dependencies are expressed by conditional probabilities that specify the probability distribution across the states of a child node for each possible combination of states of its parent nodes (Verhoeven, Arentze, Timmermans, & Waerden, 2006).

Any complete probabilistic model and hence a Bayesian network has to specify the joint probability distribution of the concerned domain (Pearl & Russell, 2001). The joint distribution is considered as the most complete probabilistic description available, since all other probabilistic measures of interest (marginal and conditional) can be computed as a follow up (Russell & Norvig, 2002).

Let a directed acyclic graph with n nodes to be defined random variable X_i ($1 \leqslant i \leqslant n$) for each node. The joint probability distribution of this network, $p(x_1, x_2, \ldots, x_n)$, is specified by the product of the individual distributions for each random variable;

$$\begin{aligned} P(x_1, x_2, \ldots, x_n) &= p(x_1) \cdot p(x2, \ldots, x_n|x_1) \\ &= p(x_1) \cdot p(x_2|x_1) \cdot p(x_3, \ldots, x_n|x_1, x_2) \ldots \\ &= p(x_1) \cdot p(x_2|x_1) \ldots p(x_n|x_1, \ldots, x_{n-1}) \end{aligned} \quad (1)$$

where x_i denotes some value of the variable X_i. This complete factorization of the distribution, also known as the general chain rule, is true for any set of random variables. Although the joint distribution grows exponentially with the size of the network, the conditional independence property of Bayesian networks allow a more compact factorization of the joint probabilities by assuming the mutual independence among the nodes (Ben-Gal, 2007). Thus, the joint product for $X = \{X_1, X_2, \ldots, X_n\}$ is given as;

$$p(x_1, x_2, \ldots, x_n) = \prod_{i=1}^{n} p(x_i|pe_i) \quad (2)$$

where pe_i denotes some set of values for X_i's parents, and $p(x_i|pe_i)$ denotes the conditional distribution for variable X_i given its parents. Heckerman (2008) warns about the possibility of the wrong order variables causing conditional independencies.

Construction of a Bayesian network follows two stages, the qualitative stage and the quantitative (probabilistic) stage (Nadkarni & Shenoy, 2004). In the qualitative stage, a cognitive approach is used to specify the structure of the graph that will show the variables of interest and their conditional dependencies. Speigelhalter, Dawid, Lauritzen, and Cowell (1993) points out that "the inference procedures in a Bayesian network are more sensitive to the qualitative structure than the quantitative probabilities associated with the structure". Bayesian networks are either based on a domain knowledge (Cinicioglu et al., 2012), or on causal maps reflecting expert ideas (Cinar & Kayakutlu, 2010; Onsel, Ulengin, & Ulengin, 2006). An alternative method is the Bayesian approach which combines expert knowledge with the data to produce improved models. In this alternative, prior knowledge is depicted from the historical data and expertise help to construct the links between the variables. In any case, probability assignment to the conditional probability functions in the network benefits both objective data (from previously analyzed database) and subjective data (expert belief) at different states of inferences.

Once the initial probabilities are given, conditional probabilities are estimated by the structured model at each state, known as posterior probabilities (Jones et al., 2010). The posterior probability of an unobserved variable $X_i \in X$ given a non-empty set of evidence $E = \{e_1, \ldots, e_m\}$ observed so far, is computed as follows;

$$P(X_i|e) = \frac{P(e|X_i) \cdot P(X_i)}{P(e)} = \frac{P(X_i, e)}{P(e)} \quad (3)$$

where $P(X_i|e)$ denotes the posterior probability distribution of variable X_i given evidence e. A Bayesian network can, therefore, be regarded as an extension of Bayes theorem to more complex problems (Keskin, Asan, & Kayakutlu, 2013).

4. Implementation of Bayesian Belief Networks

In this section implementation of Bayesian Belief Networks to measure the performance of the lean factors will be explained in several steps following the General View in Fig. 1.

Table 1
Dependency matrix with the historical probabilities.

Node dependency	TT	TF	FT	FF
Lean 9&14: 5S and Poke Yoke	0.605	0.149	0.151	0.099
Lean 11&12&13: Continuous improve	0.3	0.35	0.35	0
Lean 10&15: Clean & Waste	0.5	0.1	0.2	0.2
Lean 1&2/L9&14, L11&12&13				
Setuptime reduction & Kanban	.7	.5	.5	.3
Setuptime reduction & No Kanban	0	.1	.3	.35
No setup reduction & Kanban	.3	.3	.1	.35
No setup reduction & No Kanban	0	.1	.1	0
Lean 5/L9&14, L11&12&13, L10&15				
Continuous flow	.6	.45	.743	.4
No continuous flow	.4	.55	.257	.6
Lean 8/L9&14, L11&12&13, L10&15				
Preventive maintenance	.65	.4	.693	.10
No Preventive maintenance	.35	.6	.307	.90
Lean 7/L1&2, L5, L8				
Process flow improve	1	.25	.6	.1
No process flow improve	0	.75	.4	.9
Quality/Lean 6				
High	0.7	–	–	0.4
Low	0.3	–	–	0.6
Reliability/Lean 6				
High	.6	–	–	.4
Low	.4	–	–	.6
Flexibility/Lean 6				
High	.8	–	–	.4
Low	.2	–	–	.6
Time/Lean 7				
High	.7	–	–	.45
Low	.3	–	–	.55

4.1. Lean management and business performance criteria

After a thorough literature survey on lean manufacturing tools, the automotive industry, one of the strongest supply chains in Turkey, is chosen as the area for studying the lean techniques. The fifteen lean techniques selected by Sezen, Karakadilar, and Buyukozkan (2012) are used, as explained below:

- *Lean 1. Setup Time Reduction*: Extent to which the plant is reducing continually setup times in production (Ahmad, Schroeder, & Sinha, 2003; Koufteros, Vonderembse, & Doll, 1998; Mackelprang & Nair, 2010; Nahm, Vonderembse, & Koufteros, 2004; Sakakibara, Flynn, & Schroeder, 1993).
- *Lean 2. Pull Production/Kanban*: The extent to which production is driven by demand from the next station and ultimately from the customer, and using the features to support this system such as Kanban cards. (Ahmad et al., 2003; Koufteros et al., 1998; Nahm et al., 2004; Sakakibara et al., 1993).
- *Lean 3. Small Lot Size*: Extent to which the plant is utilizing or working towards using small lots in production (Mackelprang & Nair, 2010; Sakakibara et al., 1993).
- *Lean 4. Inventory Level*: Refers to the intention of avoiding to store excessive inventory despite the risk of not being able to meet the changing demand or of having manufacturing process disruptions (Lieberman and Demeester, 1997; Callen, Fader, & Krinsky, 2000).
- *Lean 5. Continuous Flow*: A concept whereby items are processed and moved directly from one processing step to the next, one piece at a time without waiting materials (Rooney & Rooney, 2005; Saurin et al., 2011)
- *Lean 6. Value Stream Map*: Identifying the flow of materials and information currently in the processes and activities required to bring a product to the customer from beginning to end. This is helpful to identify wastes and to decide on improvement opportunities (Duque & Cadavid, 2007; Pavnaskar, Gerhenson, & Jambekar, 2003).

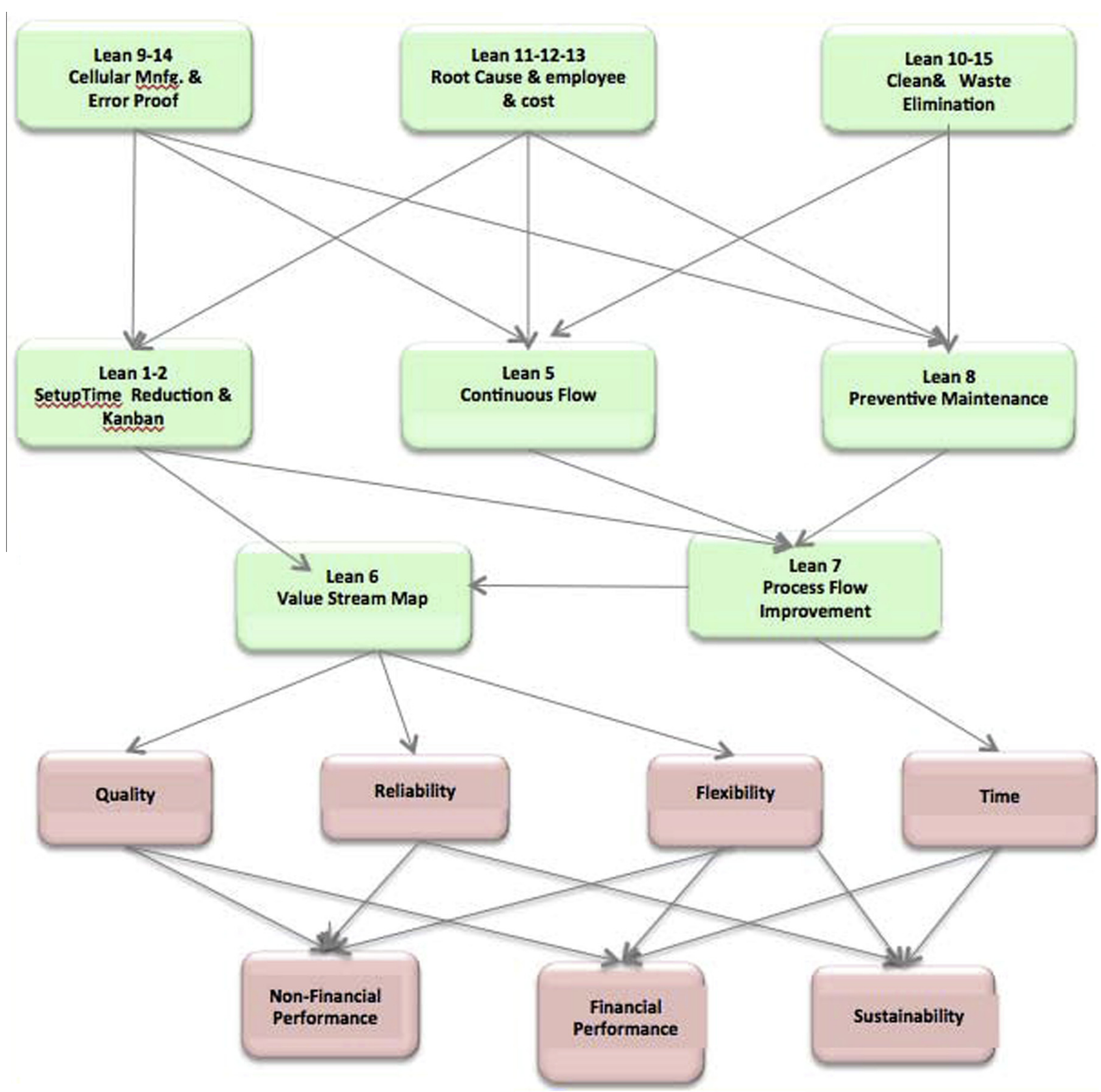

Fig. 3. Bayesian Map.

- *Lean 7. Process Flow Improvement*: Improving existing processes at the shop floor to meet new goals and objectives. Process improvement displays its results such as changing to improve quality, reduce costs (Muthu, Whitman, & Cheraghi, 1999)
- *Lean 8. Preventive Maintenance*: The extent to which equipment is routinely maintained on a proactive basis to minimize machinery downtime (Koufteros et al., 1998; Mackelprang & Nair, 2010; Nahm et al., 2004).
- *Lean 9. Cellular Manufacturing and "5S"*: The extent to which units are produced in a product oriented layout to close proximity of machinery, and use of smaller movable equipment suited for flexible floor layout (Ahmad et al., 2003; Koufteros et al., 1998; Mackelprang & Nair, 2010; Nahm et al., 2004). "5 S" is a set of principles and practices that improve the environment in the work place and quality of work life also evolves the self-discipline of teams (Duque & Cadavid, 2007).
- *Lean 10. Order and Cleanness in the Plant*: To neatly arrange and identify parts and tools for ease of use and conduct a cleanup campaign (Rooney & Rooney, 2005).
- *Lean 11. Root Cause Analysis/5 Why Analysis*: Implies the use of tools to tackle problems at work and to find solutions to problems, not to symptoms (Duque & Cadavid, 2007).
- *Lean 12. Employee Involvement*: Encouraging workers to bring production-related problems to team problem-solving sessions to define and solve problems (Koufteros et al., 1998; Sakakibara et al., 1993)
- *Lean 13. Continuous Improvement/Kaizen*: Methods are developed systematically to discipline evolution and be used to reduce defects and enhance quality (Duque & Cadavid, 2007; Koufteros et al., 1998)
- *Lean 14. Error Proof /PokeYoke*: A process used to prevent errors from occurring or to immediately point out a defect as it occurs. A "poka yoke" device is one that prevents incorrect parts from being made or assembled or flaws/errors are easily identified (Rooney & Rooney, 2005).
- *Lean 15. Waste Elimination*: It is about eliminating everything that does not add value to the production system to achieve the lowest cost production aim (Duque & Cadavid, 2007; Pavnaskar et al., 2003)

Based on the literature of performance measures for the lean factors, success components of the model are determined as flexibility, reliability, quality and time. In general, performance studies show the following three major measures; financial performance,

Non-Financial Performance/ Quality, Reliability,Flexibility

Reliability	Flexibility	Quality	High	Average	Low
High	High	High	.9	.1	0
High	High	Low	.6	.4	0
High	Low	High	.7	.3	0
High	Low	Low	0	.3	.7
Low	High	High	0	.8	.2
Low	High	Low	0	.2	.8
Low	Low	High	0	.4	.6
Low	Low	Low	0	.1	.9

Financial Performance / Quality, Flexibility,Time

Quality	Flexibility	Time	High	Average	Low
High	High	High	90	10	0
High	High	Low	70	0	30
High	Low	High	70	10	20
High	Low	Low	40	20	40
Low	High	High	60	20	20
Low	High	Low	30	10	60
Low	Low	High	40	20	40
Low	Low	Low	0	20	80

Sustainability Performance/ Flexibility,Reliability, Time

Reliability	Time	Flexibility	High	Average	Low
High	High	High	90	10	0
High	High	Low	30	60	10
High	Low	High	5	80	15
High	Low	Low	0	55	45
Low	High	High	0	90	10
Low	High	Low	0	30	70
Low	Low	High	0	20	80
Low	Low	Low	0	10	90

Fig. 4. A posteriori probabilities for Business Performances.

non-financial performance and sustainability, which are also chosen as the decision nodes of our Bayes Map.

4.2. Causal map construction

Three supply chain managers from the logistics industry are inquired to evaluate the relations among the 15 lean criteria and 4 performance criteria and 3 performance decisions. They are asked to fill in each row criterion and column criterion on a 22×22 matrix. They used the value 1 if the row criterion affects the column criterion positively (when the effect of row criterion increases than the effect of column criterion also increases); they used -1 when the row criterion affected the column criterion negatively (when row column criterion is less effective while row criterion is more effective); they used zero when no relation exists. The mode of the answers are taken to conclude and 0 is used when the answers are distributed as 1, -1 and 0. The relations are shown in Fig. 2. In this figure the arrows show the direction of effect.

This map shows that Lean Factor 9 and Lean Factor 14 are affecting each other both positively and negatively. Besides, there are certain factors like Lean 1 and Lean 2, which are dependent on each other and only affect the same factors, which can be merged. Lean factor 9 and Lean Factor 14 show exactly the same behavior. So does the Lean Factor 10 and Lean Factor 15 or Lean Factors 11–13. There are other factors like Lean 3 and Lean 4, which affect only one Lean factor but dependent on each other.

It is also observed that majority of factors are influential on Lean Factor 6, Value Maps and Lean Factor 7, Process Flow improvement directly and on others indirectly. Moreover, these two are the only ones that have a direct impact on the success factors.

Another outcome that the experts determine in the cause and effect map is that flexibility is effective on all performance achievements, time is influential on both financial performance and sustainability, quality is effective on non-financial and financial performance and reliability only affects non-financial performance and sustainability. Moreover, reliability, quality and time are effective on each other.

Finally it can be seen that non-financial performance is causing increases in the financial performance but financial performance and sustainability are influential on both sides.

4.3. Designing the Bayesian Map

The causal map is simplified on relations to create a Bayesian Map. The three supply chain managers from the industry who responded about the relations have reviewed the results in order to eliminate or combine the criteria applying the following changes:

(a) Setup time reduction and Kanban applications are taken as a combined factor;
(b) Small Lot Size and Inventory Level are directly related to manufacturing and can be eliminated for the supply chains;
(c) The root analysis, employee involvement and continuous improvements are integrated into one factor of continuous improvement;

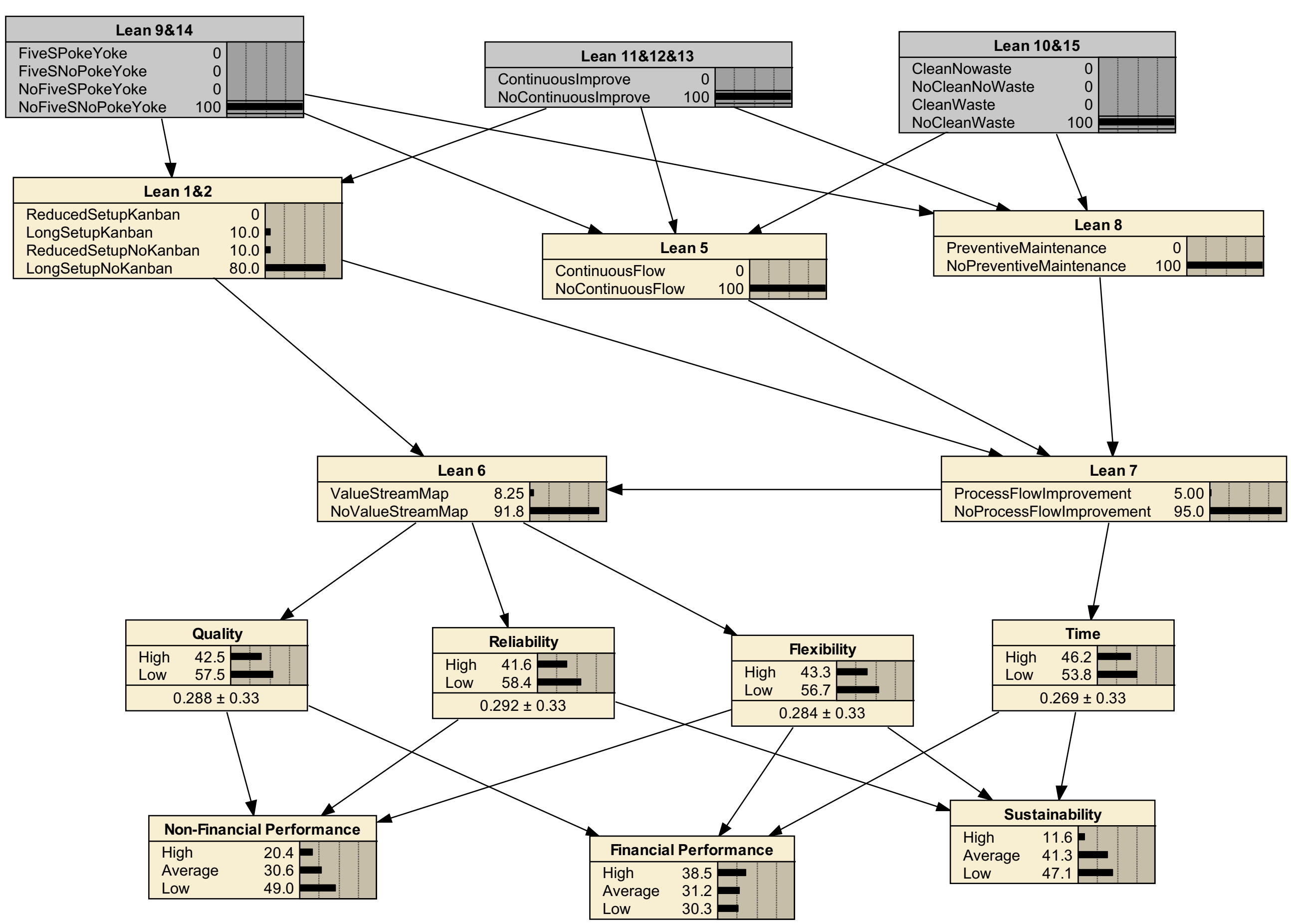

Fig. 5. Worst Case Scenario: No effective Lean Tool is used.

(d) Five S and Poke Yoke applications are combined into one factor to have any of the two;
(e) Clean and Order in the plant, and waste reduction are combined into one factor.

4.4. Prepare dependency matrices

Once the Bayesian Map is set to represent the relevance and causality, the uncertainty in the system is given with the probabilities for various situations (Dias et al., 2012). Conditional probabilities are shown with a dependence matrix.

Discussions with the supply chain experts showed that we can analyze the successful usage of a lean factor by a supplier. For example, Lean 5 represents continuous improvement and will be represented to have "Continuous improvement" or "No Continuous improvement" meaning continuous improvement is implemented in the initial choice and it is not in use in the latter. Focus on each of the 15 Lean Factors, and independence among them are studied By Karakadilar (2011). Hence, the focus probabilities for Lean 9, 10, 11, 12, 13 and 15 are taken from Karakadilar (2011) and the combination probabilities are calculated. Hence the learning is realized with historical data.

This will be represented by four different values in the combined ones. As in the combination of Lean 10 representing order and cleanness, and Lean 15 representing the waste elimination, which will have the values as "Clean Waste elimination", "Clean No waste elimination", "Not Clean Waste Elimination" and "Not Clean No waste elimination". The dependency table will be given as True–True (TT) when both are focused, True–False (TF) when the first is focused and not the second, False–True (FT) when the first is not focused but the second is and False–False (FF) when none of the factors is focused.

The matrix of dependencies is given in Table 1 for single factors and the combined factors with alternatives.

As observed in this diagram, Lean 9&14, Lean 11&12&13 and Lean 10&15 have independent probabilities. The figure shows normal probabilities taken from historical data. It can be seen that joint probabilities for Lean 7 comes from the effect of Lean 1&2, Lean 5 and Lean 8, whereas Lean 1&2 is affected by both Lean 9&10 and Lean 11&12&13; Lean 5 is affected by Lean 9&14, Lean 11&12&13 and Lean 10&15. Here Lean 7 has two options: process flow improve and no process flow improve; the probabilities are then defined as P(Lean 7/Lean 1&2, Lean 5, Lean8) which is constructed for possible combinations of different options of the three factors. Bayesian Map is shown in Fig. 3 after having reduced the relations.

Fig. 4 gives how final probabilities for financial performance and sustainability change depending on the changes in quality, reliability, flexibility and time performances.

Once the probabilities are calculated, Netica software is used to define the map and the dependency options.

4.5. Scenario analysis

The aim of the scenario analysis is to find how strong the effect of Lean Factor is on quality, reliability, flexibility and time

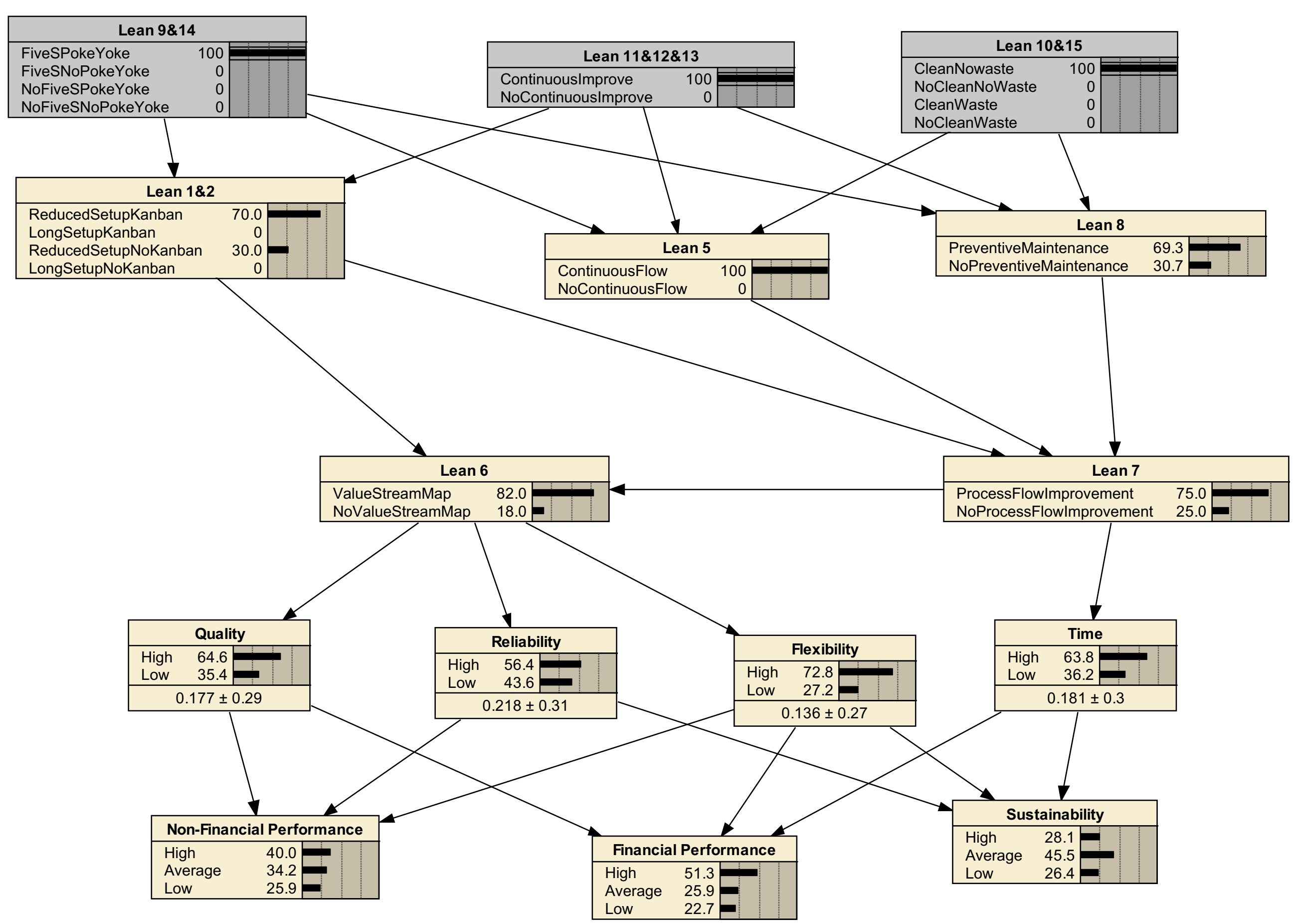

Fig. 6. Best Case Scenario: All Lean tools are used 100% effectively.

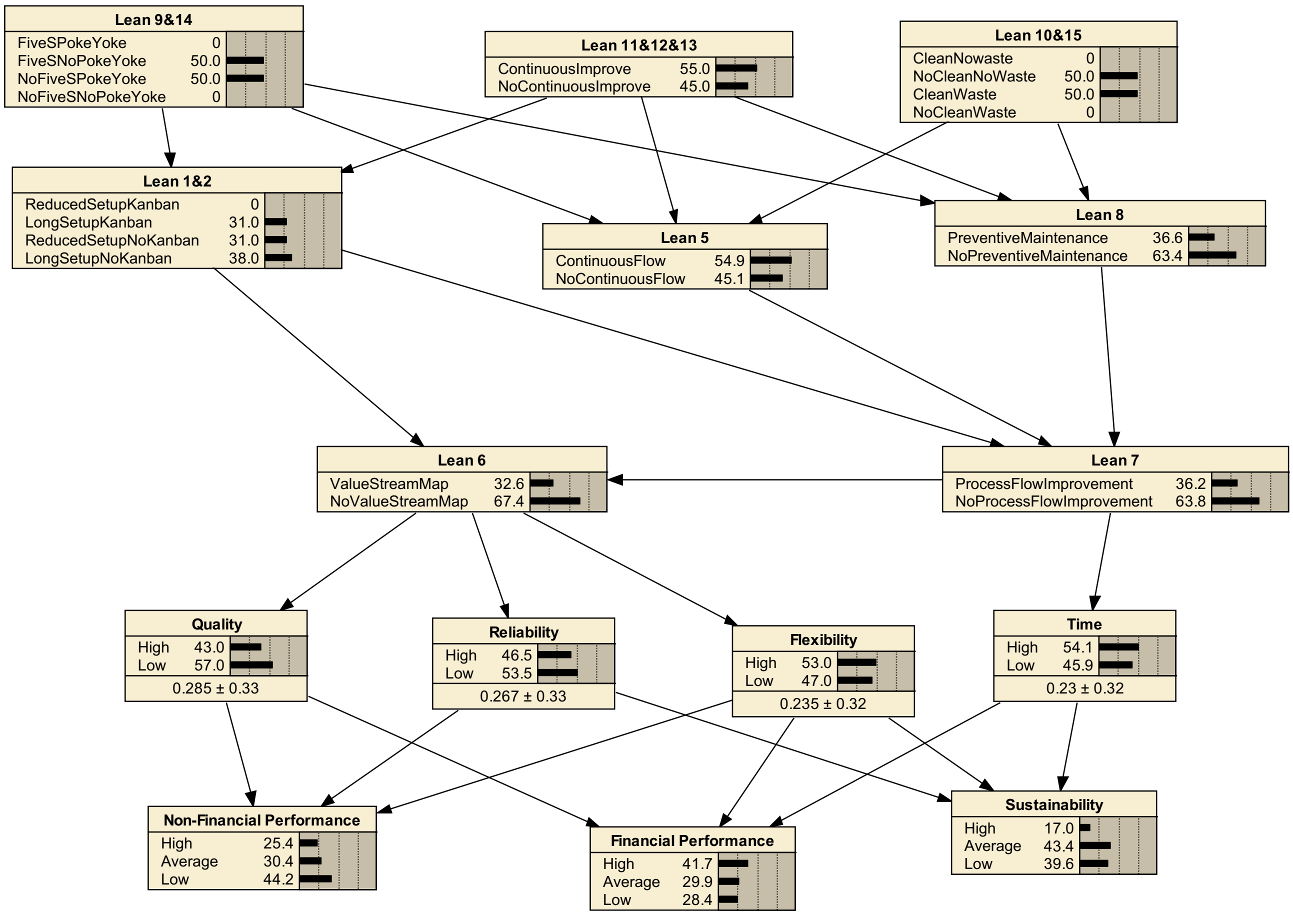

Fig. 7. Scenario 3-Only one of the combined tools are used.

components so that the performance expectations can be built more realistically. The normal probabilities taken from Karakadilar (2011) represent the first scenario.

In all the scenarios, normalized probabilities are used and no error is assumed to occur in the inferences ($\varepsilon = \varnothing$), as Kjærulff and Madsen (2008) suggests. (See Figs. 5 and 6)

The normalized probability value for this particular example is 0.675, meaning that if there is a high need for lean tools, it will provide convincing evidence of high performance. Another particular type of probabilistic inference task is to compute the (prior) marginal probability, $P(X_i)$, of a variable X_i in the network. In this case, Eq. (3)does not incorporate evidence into the inference task, i.e. it is assumed that $\varepsilon = \varnothing$ (Kjærulff & Madsen, 2008).

There are three scenarios prepared as the worst scenario, the best scenario and the average scenario which are explained in detailed as below.

SCENARIO 1: Worst Case is designed as not implementing the most effective lean tools. In this case no 5S or No Poke Yoke is applied, no Continuous improvement is implemented and the plant layout is not in order or cleanness required, while waste removal is not cared about at all. It is immediately observed in Fig. 7 that Lean1&2 is not fully dependent on the root factors, hence the Kanban application still has a 10% possibility of application. Obviously No Continuous Flow or Preventive Maintenance applications will be possible at all. However there is an 8.25% possibility to use Value Stream Maps and 5% possibility to apply process flow improvements independently. We can conclude that both Kanban and Value stream Maps are the most independent tools in the lean implementation.

These possibilities obviously lead to a low quality with a probability of 57.5%, low reliability with a probability of 56.7% and low time performance with a probability of 53.8%. It is observed that there is still a 38.5% chance of having high Financial Performance possibly by price reductions but there is only 20.4% probability to have high Non-Financial Performance or only 11.6% probability to have high performance in sustainability.

When compared with the Scenario 1, there are remarkable drops of 11–16% in final performances. This scenario shows that application of lean tools have an important influence on financial and non-financial performances.

SCENARIO 2: Best Case: Both 5S and Poke Yoke are applied without any doubt, Continuous Improvement is implemented 100% effectively and the order and cleanness of the plant is perfect and all the waste is removed. This is an idealistic situation, which hardly can ever be true. Even if implemented, the final performances do not change a lot. When compared with the real case in Scenario 1, there is only an improvement of 2–5% in performances. The impressive difference of 13–20% between the worst case and the best case is to be taken serious.

SCENARIO 3: Average Scenario: This case is closer to reality where;

(a) The combined tools are considered to include only one tool instead of both, e.g. either 5S or Poke Yoke is applied, but not both.
(b) The second and third level Lean Tools are allowed to have a small percentage of independent effect, e.g. Continuous Flow might be used 30% effectively even though 5Spoke Yoke,

Continuous Improvement or cleanness or Waste removal do not exist. Another Example is that the Value Stream Map can be used all alone even though none of the previous tools are applied by a probability of 30%.

These assumptions are against the will of the field experts we interviewed, but in line with the observations of the academic experts. This scenario is considered as the most realistic scenario for the case in Turkey (Fig. 7).

It is clearly observed that none of the lean tools are implemented and used with 100% effectiveness. They are assumed to have average use, some do not exist at all and some are used with an average influence. This is the case when quality and reliability components are kept low with a probability of more than 0.50; and hence, the probability of achieving a high Non-Financial Performance is only 25.4%. It is not lower because flexibility can still be high by a possibility of 53%.

Financial Performance seems to drop only by 7% compared to initial calculations, mainly due to the drop in quality, since the time component can also perform highly by 54.1% of probability. This is the case where monetary terms have to be analyzed in detail.

Sustainability shows a 7% drop compared to Scenario 1, but seems to have the highest possibility of showing average performance. This achievement clearly shows high dependence of sustainability on the time and flexibility components.

4.6. Business Implications of the obtained results

Bayes Belief Network tool is applied on fifteen lean factors that are observed to be effective in the Turkish automotive industry. It is observed that the increase of high non-financial performance with 100% effective use of integrated lean factors may grow up to 16%. Increases in high financial performance may vary by 20% and increases in high sustainability changes between 5–23%. This allows us to conclude that effective use of lean tools in the Turkish automotive sector increases business performance without doubt. A variety of implementing some lean factors with low success and others with high effectiveness is studied to test the robustness of the achieved impacts. The fact that flexibility can be still held high when all the factors are in effect, does not allow non-financial performance to drop.

With all the four scenarios analyzed in this study, it can be concluded that even a moderately effective use of lean manufacturing tools can cause changes in financial or non-financial performances and the sustainability of the company.

5. Conclusions and perspectives

Scenarios can be driven by events or problems that may arise from a company's portfolio of business lines and risks. Event-driven scenarios are based on plausible events and the effect of events on the firm. Portfolio-driven scenarios are based on the vulnerabilities of the portfolio held by a firm. Scenario analysis with the a posteriori (after event is realized) probabilities has become a preferred tool in the business world with uncertainties. Since the economic crisis of 2010, hard to measure performance criteria like sustainability or competence are measured by using scenarios to define better policies. Furthermore, sensitivity analyses can be done using the scenario analyses.

This paper designs and implements a Bayesian Belief Network Model to demonstrate the effect of different lean management tools on the business performance. The influence among the lean factors and the performance components are determined through Delphi analysis with experts. Four scenarios are implemented. The first one is using the probabilistic data found by factor analysis of an SME survey in Turkey. The second one is the worst case scenario where no major lean tool is used. It is observed that between the two scenarios there is a considerable drop of 10–25% in performance probabilities. It is also observed that sustainability is the most affected component. In the third scenario, the best case scenario is analyzed, where most of the lean tools are used and the performances are increased only by 5% compared to the first scenario. The fourth scenario can be seen as the more realistic one, since it differs from the initial scenario by using only one of the combined lean tools. Non-financial performance is affected most when the last scenario is used since the drop of probability of having high non-financial performance has dropped by 12% while financial performance and sustainability dropped only by 7%. All these analyses are evidences of lean manufacturing tools causing changes in the business performances though positive or negative changes never exceed 20%.

This study contributes to intelligent business management approaches by showing that lean factors have considerable impact on the improvement of sustainability and performance of the non-financial factors. The impact of implementing any Lean Factor on the financial factors is seen relatively small. These observations are made only for the case study among the automotive supply chain. It should be repeated for supply chains in other industries to generalize the solutions.

Real data could not be collected in this application because companies in the study did not collect lean application related data. In the future the data will be collected to repeat the analysis with real data and compare the ANN and Fuzzy analytics on the lean implementations.

Following the generalization of the model, and validation with the real data an expert system for business performance measure can be developed.

Acknowledgments

We would like to present our gratitude for all the contributions given by academic experts in the field and business experts of Turkish automotive industry. This study would not be realized without the input of experts who worked with us. The authors thank the Editor, Professor Binshan Lin, and anonymous reviewers for their valuable comments and suggestions to improve the early version of the paper.

References

Achanga, P., Shehab, E., Rajkumar, R., & Nelder, G. (2012). A fuzzy-logic advisory system for lean manufacturing within SMEs. *International Journal of Computer Integrated Manufacturing, 25*(9), 839–852.

Adusei-Poku, K., Van den Brink, G. J., & Zucchini, W. (2007). Implementing a Bayesian network for foreign exchange settlement: A case study in operational risk management. *Journal of Operational Risk, 2*(2), 101–107.

Ahmad, S., Schroeder, R. G., & Sinha, K. K. (2003). The role of infrastructure practices in the effectiveness of JIT practices: Implications for plant competitiveness. *Journal of Engineering and Technology Management, 20*(3), 161–191.

Allwood, J. M., Laursen, S. E., Russell, S. N., Malvido de Rodríguez, C., & Bocken, N. M. P. (2008). An approach to scenario analysis of the sustainability of an industrial sector applied to clothing and textiles in the UK. *Journal of Cleaner Production, 16*(12), 1234–1246.

Amin, M. A., & Karim, M. A. (2013). A time-based quantitative approach for selecting lean strategies for manufacturing organisation. *International Journal of Production Research, 51*(4), 1146–1167.

Antón, A., McCracken, W. M., & Potts, C. (1994). Goal decomposition and scenario analysis in business process reengineering. *Advanced Information Systems Engineering, 811*, 94–104.

Bañuls, V. A., & Turoff, M. (2011). Scenario construction via Delphi and cross-impact analysis. *Technological Forecasting and Social Change, 78*(9), 1579–1602.

Ben-Gal, I. (2007). Bayesian networks. In F. Ruggeri, F. Faltin, & R. Kenett (Eds.), *Encyclopedia of statistics in quality & reliability* (pp. 1–6). Wiley & Sons.

Blackmond, K. (1995). Sensitivity analysis for probability assessments in Bayesian networks. *IEEE Transactions On Systems Man and Cybernetics, 25*(6), 901–909.

Borth, M. (2002). Learning from multiple Bayesian networks for the revision and refinement of expert systems, In: Jarke, M; Koehler, J; Lakemeyer, G. (Eds), *Lecture Notes in Artificial Intelligence*, 2479, 82–96.

Bortolotti, T., Danese, P., & Romano, P. (2013). Assessing the impact of just-in-time on operational performance at varying degrees of repetitiveness. *International Journal of Production Research, 51*(4), 1117–1130.

Brinckmann, J., Grichnik, D., & Kapsa, D. (2010). Should entrepreneurs plan or just storm the castle? A meta-analysis on contextual factors impacting the business planning–performance relationship in small firms. *Journal of Business Venturing, 25*(1), 24–40.

Callen, J. L., Fader, C., & Krinsky, I. (2000). Just-in-time: A cross-sectional plant analysis. *International Journal of Production Economics, 63*(3), 277–301.

Camacho-Miñano, M., Moyano-Fuentes, J., & Sacristán-Díaz, M. (2012). What can we learn from the evolution of research on lean management assessment? *International Journal of Production Research, 51*(4), 1098–1116.

Celeux, G., Corset, F., Lannoy, A., & Ricard, B. (2006). Designing a Bayesian network for preventive maintenance from expert opinions in a rapid and reliable way. *Reliability Engineering and System Safety, 91*, 849–856.

Chai, J., Liu, J. N. K., & Ngai, E. W. T. (2013). Application of decision-making techniques in supplier selection: A systematic review of literature. *Expert Systems with Applications, 40*(10), 3872–3885.

Chuanzhe, L., & Fengping, S., (2006). The review of operational risk measuring models (ID: 5–038). In: X.Y. Wang & J. Shen (Eds.), *Proceedings of the13th international conference on industrial engineering and engineering management, Vols 1–5, International conference on industrial engineering and engineering management IEEM* (pp. 1823–1827), published by Shandong Univ, Weihai, PEOPLES R CHINA.

Cinar, D., & Kayakutlu, G. (2010). Scenario analysis using Bayesian networks: A case study in energy sector. *Knowledge-Based Systems, 23*(3), 267–276.

Cinicioglu, E. N., Sahin, S. O., & Ülengin, F. (2012). Competitiveness analysis of automotive industry in Turkey using Bayesian networks. *Expert Systems with Applications, 39*(12), 10923–10932.

Cuatrecasas, L. (2004). A lean management implementation method in service operations. *International Journal of Services Technology and Management, 5*(5–6), 532–544.

Daniel, B. K., McCalla, G. I., & Schwier, R. A. (2007). Bayesian belief network approach for analysis of intercultural collaboration in virtual communities using social capital theory. In: T. Ishida & Fussell (eds), *Lecture notes in computer science*, 4568, 291–305.

Danks, D. (2002). Learning the causal structure of overlapping variable sets. *Lecture Notes In Computer Science, 2534*, 178–191.

Das, S., & Lawless D. (2002). Trustworthy situation assessment via belief networks. In: *Proceedings of the fifth international conference on information fusion*, Vol. 1, (pp. 543–549).

Dennis, S., King, B., & Hind, M. et al. (2000). Applications of business process simulation and lean techniques in British Telecommunications PLC, In: *Proceedings of The 2000 Winter Simulation Conference*, 1–2, (pp. 2015–2021).

Detty, R. B., & Yingling, J. C. (2000). Quantifying benefits of conversion to lean manufacturing with discrete event simulation: a case study. *International Journal of Production Research, 38*(2), 429–445.

Dias, S., Sutton, A. J., & Welton, N. J. (2012). Embedding evidence synthesis in probabilistic cost-effectiveness analysis. *Medical Decision Making, 33*(5), 671–678.

Dinwoodie, I., McMillan, D., & Revie, M. et al. (2013). Development of a Combined Operational and Strategic Decision Support Model for Offshore Wind, In: J. Tande, T. Kvamsdal, & M. Muskulus (Eds), *Energy Procedia*, Vol. 35 (pp. 157–166), Published Norway, 2013.

Dong, L., Cheng, W., Bao, H., & Yang, Y. (2010). Probabilistic load flow analysis for power system containing wind farms. In: *Proceedings oft the IEEE power and energy engineering conference (APPEEC)* (pp. 1–4).

Duque, D. F. M., & Cadavid, L. R. (2007). Lean manufacturing measurement: The relationship between lean activities and lean metrics. *Estudios Gerenciales, 23*(105), 69–83.

Fabian, R., Cristhian, B., Ricardo, C., Diego, et al. (2010). Efficiency measurement of research groups using data envelopment analysis and Bayesian networks. *Scientometrics, 83*(3), 711–721.

Falcon, R., & Abielmona, R. (2012). A Response-aware risk management framework for search-and-rescue operations, In: *2012 IEEE congress on evolutionary computation (CEC): IEEE Congress on Evolutionary Computation*.

Gregoriades, A., & Sutcliffe, A. (2008). A socio-technical approach to business process simulation. *Decision Support Systems, 45*(4), 1017–1030. Special Issue.

Groth, S. S., & Muntermann, J. (2011). An intraday market risk management approach based on textual analysis. *Decision Support Systems, 50*(4), 680–691.

Hager, D., & Andersen, L. B. (2010). A knowledge based approach to loss severity assessment in financial institutions using Bayesian networks and loss determinants. *European Journal of Operational Research, 207*(3), 1635–1644.

Hamilton, G., Alston, C., & Chiffings, T. et al. (2005). Integrating Science through Bayesian Belief Networks: Case study of Lyngbya in Moreton Bay, In: A. Zerger, R.M. Argent (Eds), *Proceedings of international congress on modelling and simulation (MODSIM05)*, Melbourne, Australia, December 12–15 (pp. 392–399).

Hammond, T. R. (2004). A recipe for Bayesian network driven stock assessment. *Canadian Journal of Fisheries and Aquatic Sciences, 61*(9), 1647–1657.

Hänninen, M., Valdez Banda, O. A., & Kujala, P. (2014). Bayesian network model of maritime safety management. *Expert Systems with Applications, 41*(17), 7837–7846.

Harries, C. (2003). Correspondence to what? Coherence to what? What is good scenario-based decision making? *Technological Forecasting & Social Change, 70*, 797–817.

Heckerman, D. (2008). A tutorial on learning with bayesian networks. In E. H. Dawn & C. J. Lakhmi (Eds.), *Innovations in Bayesian networks: Theory and applications*. Berlin Heidelberg: Springer-Verlag.

Hofer, C., Eroglu, C., & Hofer, A. R. (2012). The effect of lean production on financial performance. the mediating role of inventory leanness. *International Journal of Production Economics, 138*(2), 242–253.

Hosseini, N. H., Aliheidari, T., & Khademi, Z. T. (2012). Finding a probabilistic approach to analyze lean manufacturing. *Journal of Cleaner Production, 29–30*, 73–81.

Hristea, F., & Colhon, M. (2012). Feeding syntactic versus semantic knowledge to a knowledge- lean unsupervised word sense disambiguation algorithm with an underlying naive bayes model. *Fundamenta Informaticae, 119*(1), 61–86.

Jiang, G. P., & Chen, Y. W. (2004). Identification of critical risk factors in software project risk management, In: Q. R. Xu, X. B. Wu, & J. Chen (Eds), *Proceedings of 4th international conference on management of innovation and technology location: Hangzhou, Peoples R. China*, Oct. 24–26, 2004 (pp. 211–215), published by Res Ctr Innovat & Dev, Zhejiang Univ, Chinese Acad Sci, NSFC; State Minist Educ, TRIUMF, China.

Jones, B. J., Jenkinson, I., Yang, Z., & Wang, J. (2010). The use of Bayesian network modelling for maintenance planning in a manufacturing industry. *Reliability Engineering & System Safety, 95*, 267–277.

Karakadilar, I. S. (2011). *Modelling and analysis of the role of leanness in the supply chain relations in the turkish automotive industry (in Turkish)* (Ph.D. Thesis), Gebze Institute of Technology.

Keskin, C., Asan, U., & Kayakutlu, G. (2013). *Value stream maps for industrial energy efficiency*. In F. Cavallaro (Ed.). *Assessment and simulation tools for sustainable, energy systems, green energy and technology* (129). http://dx.doi.org/10.1007/978-1-4471-5143-2_17. Chapter 17.

Khorram, A., Ping, C. W., & Hui, L. T. (2011). Causal Knowledge-Driven Approach For Stock Analysis, In: S. Juan (Ed.), *Proceeding of international conference on business and economics research (ICBER 2010, Kuala Lumpur, Malaysia, Nov 26–28, 2010, Business and Economics Research Book Series: International proceedings of economics development and research Vol. 1* (pp. 366–371), published in Malaysia.

Kisioglu, P., & Topcu, Y. I. (2011). Applying Bayesian Belief Network approach to customer churn analysis: A case study on the telecom industry of Turkey. *Expert Systems With Applications, 38*(6), 7151–7157.

Kjærulff, U. B., & Madsen, A. L. (2008). *Bayesian networks and influence diagrams: A guide to construction and analysis*. USA: Springer.

Koufteros, X. A., Vonderembse, M. A., & Doll, W. J. (1998). Developing measures of time-based manufacturing. *Journal of Operations Management, 16*(1), 21–41.

Kull, T. J., Yan, T., Liu, Z., & Wacker, J. G. (2014). The moderation of lean manufacturing effectiveness by dimensions of national culture: Testing practice-culture congruence hypotheses. *International Journal of Production Economics, 153*, 1–12.

Landuyt, D., Broekx, S., D'hondt, R., Engelen, R. G., Aertsens, J., & Goethals, P. (2013). A review of Bayesian belief networks in ecosystem service modelling. *Environmental Modelling & Software, 46*, 1–11.

Lee, C., Song, B., & Cho, Y. et al. (2010). A bayesian belief network approach to operationalization of multi-scenario technology roadmap, In: D. F. Kocaoglu, T. R. Anderson, & T. U. Daim (Eds), *Proceedings of portland international center for management of engineering and technology (PICMET 10)*, Natl Elect & Comp Technol Ctr (NECTEC), Natl Sci & Technol Dev Agcy (NSTDA), Portland, OR, 2010.

Lei, Z., Pijanowski, B. C., Alexandridis, K. T., et al. (2005). Distributed modeling architecture of a multi-agent-based behavioral economic landscape (MABEL) model. *Simulation-Transactions of the Society for Modeling and Simulation International, 81*(7), 503–515.

Li, Y., Rajpal, G., Sawhney, R., & Li, X. (2009). Enhancing lean sustainability via bayesian network techniques, In: *Proceedings of the 2009 industrial engineering research conference*. Miami, FL: 1171–1178.

Li, Y., Sawhne, R. S., & Wilck, J. H. (2013). Applying Bayesian network techniques to prioritize lean six sigma efforts. *International Journal of Strategic Decision Sciences, 4*(2), 1–15.

Macedo, P., & Camarinha-Matos, L. M. (2013). A qualitative approach to assess the alignment of Value Systems in collaborative enterprises networks. *Computers & Industrial Engineering, 64*(1), 412–424.

Mackelprang, A. W., & Nair, A. (2010). Relationship between just-in-time manufacturing practices and performance. a meta-analytic investigation. *Journal of Operations Management, 28*(4), 283–302.

Marcot, B. G. (2012). Metrics for evaluating performance and uncertainty of Bayesian network models. *Ecological Modelling, 230*, 50–62.

Meade, D. J., Kumar, S., & White, B. (2010). Analysing the impact of the implementation of lean manufacturing strategies on profitability. *Journal of The Operational Research Society, 61*(5), 858–871.

Medina, L. A., Jankovic, M., Okudan Kremer, G. E., & Yannou, B. (2013). An investigation of critical factors in medical device development through Bayesian networks. *Expert Systems with Applications, 40*(17), 7034–7045.

Muthu, S., Whitman, L. & Cheraghi, S. H. 1999. Business process reengineering: a consolidated methodology [online]. <http://webs.twsu.edu/whitman/papers/ijii99muthu.pdf> [Accessed April 2013].

Nadkarni, S., & Shenoy, P. P. (2004). A causal mapping approach to constructing bayesian networks. *Decision Support Systems, 38*(2), 259–281.

Nahm, A. Y., Vonderembse, M. A., & Koufteros, X. A. (2004). The impact of organizational culture on time-based manufacturing and performance. *Decisions Sciences, 35*(4), 579–607.
Olhager, J., & Prajogo, D. I. (2012). The impact of manufacturing and supply chain improvement initiatives: a survey comparing make-to-order and make-to-stock firms. *Omega-International Journal of Management Science, 40*(2), 159–165.
Oliver, N., Schab, L., & Holweg, M. (2007). Lean principles and premium brands: conflict or complement? *International Journal of Production Research, 45*(16), 3723–3739.
Onsel, S. S., Ulengin, F., & Ulengin, B. (2006). A Bayesian causal map for inflation analysis: The case of Turkey. *European Journal of Operational Research, 175*(2), 1268–1284.
Pavnaskar, S. J., Gerhenson, J. K., & Jambekar, A. B. (2003). Classification scheme for lean manufacturing tools. *International Journal of Production Research, 41*(13), 3075–3090.
Pearl, J., & Russell, S. (2001). Bayesian networks. In M. Arbib (Ed.), *Handbook of Brain Theory and Neural Networks* (pp. 157–160). Cambridge: MIT Press.
Pengfei, G., & George, Z. Z. (2013). Strategic queueing behavior and its impact on system performance in service systems with the congestion-based staffing policy. *Manufacturing & Service Operations Management, 15*(1), 118–131.
Perkusich, M., Soares, G., Almeida, H., & Perkusich, A. (2015). A procedure to detect problems of processes in software development projects using Bayesian networks. *Expert Systems with Applications, 42*(1), 437–450.
Pollino, C. A., & White, A. K. (2005). Development and application of a bayesian decision support tool to assist in the management of an endangered species. In: A. Zerger, & R. M. Argent (Eds), *Proceedings of international congress on modelling and simulation (MODSIM05)*, Melbourne, Australia, Dec. 12–15, 2005, Advances And Applications For Management And Decision Making (pp. 2089–2095).
Pradhan, S., Singh, R., & Kachru, K. et al. (2007). A Bayesian network based approach for root-cause-analysis in manufacturing process, In: Y. Wang, Y. M. Cheung, & Q. Zhang (Eds), *Proceedings of international conference on computational intelligence and security*, Harbin, Peoples R China, Dec. 15–19, 2007, (pp. 10–14).
Ramesh, V., & Kodali, R. (2012). A decision framework for maximising lean manufacturing performance. *International Journal of Production Research, 50*(8), 2234–2251.
Rodger, J. A. (2014). 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. *Expert Systems with Applications, 41*(16), 7005–7022.
Rooney, S. A., & Rooney, J. J. 2005. Lean glossary [online]. Available from: <http://www.qualityprogress.asq.org/pub/qualityprogress/past/0605/qp0605rooney.pdf> [Accessed April 2014].
Rubio, S., & Corominas, A. (2008). Optimal manufacturing-remanufacturing policies in a lean production environment. *Computers & Industrial Engineering, 55*(1), 234–242.
Russell, S. J., & Norvig, P. (2002). *Artificial Intelligence. a modern approach (2nd ed.)*. Prentice-Hall, ISBN 0137903952.
Sakakibara, S., Flynn, B. B., & Schroeder, R. G. (1993). A framework and measurement instrument for just-in-time manufacturing. *Production and Operations Management, 2*(3), 177–194.
Santos, E. E., Santos, E. Jr., & Wilkinson, J.T., et al. (2011). Modeling Complex Social Scenarios Using Culturally Infused Social Networks, In: *Proceedings of ieee international conference on systems, man and cybernetics (SMC)*, Anchorage, AK Oct. 09–12, 2011, (pp. 3009–3016).
Sarkis, J., & Dhavale, D. G. (2015). Supplier selection for sustainable operations: A triple-bottom-line approach using a Bayesian framework, *International Journal of Production Economics*, In Press, Available online: <www.sciencedirect.com>.
Saurin, T. A., Marodin, G. A., & Ribeiro, J. L. D. (2011). A framework for assessing the use of lean production practices in manufacturing cells. *International Journal of Production Research, 49*(11), 3211–3230.
Sezen, B., Karakadilar, I. S., & Buyukozkan, G. (2012). Proposition of a model for measuring adherence to lean practices: applied to Turkish automotive part suppliers. *International Journal of Production Research, 50*(14), 3878–3894.
Sharad, B., Siddharth, S. S., & Dipak, C. J. (2008). Customer lifetime value measurement. *Management Science, 54*(1), 100–112.
Shen, C-w. (2008). Assessing the financial risks of e-logistics implementation in transport and logistics sectors, in J. P. Li, L. Yu, L. D. Zhao (Eds), In: *Proceedings of international conference on e-risk management (ICeRM 2008)*, SE Univ, Inst Syst Engn, Nanjing, Peoples R China, Jun. 27–30, 2008, Sponsor(s): Operat Res Soc China, Decis Sci Branch; CSOOPEM, Youth Branch; Univ Toronto, Risk China Res Ctr; Syst Engn Soc China, Advances in Intelligent Systems, (pp. 14–19).
Singh, R. K., Kumar, S., Choudhury, A. K., & Tiwari, M. K. (2006). Lean tool selection in a die casting unit: a fuzzy-based decision support heuristic. *International Journal of Production Research, 44*(7), 1399–1429.
Speigelhalter, D. J., Dawid, A. P., Lauritzen, S. L., & Cowell, R. G. (1993). Bayesian analysis in expert systems. *Statistical Science, 8*(3), 219–247.
Stewart, T. J., French, S., & Rios, J. (2013). Integrating multicriteria decision analysis and scenario planning — review and extension. *Omega-International Journal of Management Science, 41*(4), 679–688.
Sun, L. L., & Shenoy, P. P. (2007). Using Bayesian networks for bankruptcy prediction: Some methodological issues. *European Journal of Operational Research, 180*(2), 738–753.
Suryani, E., Chou, S.-Y., Hartono, R., & Chen, C-H. (2010). Demand scenario analysis and planned capacity expansion: A system dynamics framework. *Simulation Modelling Practice and Theory, 18*(6), 732–751.
Tan, Y., & Takakuwa, S. (2007). *Predicting the impact on business performance of enhanced information system using business process simulation. Proceedings of the 39th conference on Winter simulation: 40 years!* Washington D.C.: IEEE Press. 2203-2211.
Trucco, P., Cagno, E., & Grande, O., et al. (2006). A Bayesian Approach for integrating organisational factors in risk analysis: A case study in maritime, In: C. G. Soares, E. Zio (Eds), *proceedings of european safety and reliability conference (ESREL 2006), Estoril, Portugal, SEP 18-22, Proceedings and monographs in engineering, water and earth sciences* (pp 443-450).
Ulengin, F., Kabak, O., Onsel, S., et al. (2010). A problem-structuring model for analyzing transportation-environment relationships. *European Journal of Operational Research, 200*(3), 844–859.
Ulengin, F., Onsel, S., Topcu, Y. I., Aktas, E., & Kabak, O. (2007). An integrated transportation decision support system for transportation policy decisions: The case of Turkey. *Transportation Research Part A, 41*, 80–97.
Verhoeven, M., Arentze, T. A., Timmermans, H. J. P., & Waerden, P. J. H. J. van der. (2006). Modeling consumer choice behaviour with Bayesian belief Networks, In: *Proceedings of the RARCS conference*, Budapest, Hungary, 18.
Vinodh, S., & Aravindraj, S. (2013). Evaluation of leagility in supply chains using fuzzy logic approach. *International Journal of Production Research, 51*(4), 1186–1195.
Vinodh, S., & Joy, D. (2012). Structural equation modelling of lean manufacturing practices. *International Journal of Production Research, 50*(6), 1598–1607.
Vlachos, I., & Bogdanovic, A. (2013). Lean thinking in the European hotel industry. *Tourism Management, 36*, 354–363.
Womack, J. P. (2004). An action plan for lean services. Lean service summit Europe 2004. Amsterdam.
Womack, J. P., & Jones, D. T. (1996). *Lean thinking*. New York: The Free Press.
Womack, J. P., Jones, D. T., & Roos, D. (1990). *The machine that changed the world: the story of lean production*. New York: Harper Collins.
Wong, W. P., & Wong, K. Y. (2007). Supply chain performance measurement system using DEA modeling. *Industrial Management & Data Systems, 107*(3), 367–381.
Yang, M. G., Hong, P., & Modi, S. B. (2011). Impact of lean manufacturing and environmental management on business performance. an empirical study of manufacturing firms. *International Journal of Production Economics, 129*(2), 251–261.
Zhang, L., Wu, X., Ding, L., Skibniewski, M. J., & Yan, Y. (2013). Decision support analysis for safety control in complex project environments based on Bayesian Networks. *Expert Systems with Applications, 40*(11), 4273–4282.