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Measuring Effect of Supply Chain Design on Firm Performance Using Bayesian Networks

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Abstract

The profitability of a firm depends significantly on Supply Chain Design of a firm and it can be measured using the SCOR metrics. So it is important to understand the various factors that quantify the SC design of a firm. Identifying the most important factors which lead to affect firm's performance significantly would help to make strategies which would help to improve firm's performance. The paper aims to design a Bayesian model using the variables of the SCOR metrics and effect of these variables on firm's revenue. Bayesian belief network (BBN) modeling are used to provide a framework for measuring impact of SCOR metrics variables on firm's revenue. Bayesian methodology provides the reasoning in causal relationship among various variables and incorporates the both objective and subjective data.

This paper presents a causal relationship among various variables in a SCOR metrics and firm's revenue. The most important factor which largely affects the firm's revenue is Return On Assets and is quite intuitive. Other Factors, On time and in full, Perfect order delivery order fulfillment lead time, supply chain response and COGS to have small impact on revenue.

Capability of Bayesian networks while modeling in uncertain conditions, provides a prefect platform for analyzing the risk factors. BBN provides a more robust method for studying the impact or predicting various risk factors.

The major contribution of this paper is to develop a quantitative model for SCOR variables effect on firm's revenue. This model can be updated when a new data arrives.

Keywords: Supply Chain, SCOR Metrics, Bayesian networks.

Introduction

A supply chain consists if all the parties and people involved in fulfilling customer request directly or indirectly (Mentzer, 2001). A supply chain includes the suppliers, manufacturer, transporters, warehouses, customers and retailers. In short, a supply chain is a system comprising of people, technologies, organizations, information, resources and activities involved in moving products or services from suppliers to customers (CSCMP, 2012).

Supply Chain Council developed the Supply Chain Operations Reference Model (SCOR). SCOR model has been very effective in measuring the performance of supply chain(SC) design of the firm. The variables of the SCOR metrics are very important indicators of the SC design.

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This paper will try to provide a modeling approach to find the effect of the variables of the SCOR metrics on the firm's revenue. In order to understand the causal links between various variables of the SCOR metrics and the firms revenue, a Bayesian Network(BN) is developed in which every variable of a SCOR metrics is presented as a node with directed links forming arcs between the variables as dependent factors and firm's revenue as independent factor. The presentation of the interactions among the variables as independent factors and firm's revenue as dependent factor is the key point of BNs and allows the identification of factors which have major impact on the firm's revenue.

Potential advantages of Bayesian Networks compared with other approaches (Network Based Approaches, Principal-Agent Approaches, Behavioral Approaches, Stochastic Models) to modelling SCOR metrics variables include the compact representation, the robustness to small alterations of the model, the ability to operate with different variable types, the facilitation of prior knowledge, the ability to handle incomplete data sets, and a form of learning can be used. A security risk analysis model using Bayesian network was proposed by Feng et al. (2014). In the following paper in section 2, we present the study about SCOR and its significance. In section 3, we provide a brief overview of Bayesian belief network (BBN) modeling. In section 4, we present the details of our model. In section 5, proposed model is tested through a illustrative example, and present the results and sensitivity analysis to identify the critical variables in SCOR model. In section 6, we provided the managerial implication and limitations of this research study. The last section of the paper discusses the conclusions and future scope of research.

Literature Review

A firm is accountable to its shareholders, customers, and stakeholders. Sustainability and predictability of business outcomes derive the real or perceived value of the business (Sushil, 2016). The SCOR is very helpful in refining strategy, making the structure, processes management, and performance measure. An organization's annual strategic priorities are perceived in SCOR's horizontal process integration with its vertical process integration.

Organizations that used SCOR to improve their supply chain to redesign process, or business process engineering, have shown that SCOR is an effective enabler for aligning an organization's portfolio of improvement projects with strategic goals and objectives (Lockamy & McCormack, 2004). SCOR is highly effective in solving top five supply chain challenges viz. superior customer service, cost control, planning and risk management, supplier/partner relationship management and talent.

Supply Chain Council developed SCOR, which is a non-profitable and independent corporation originated in 1996. It started just with 69 firms and now it has around 1000 members. It aims at developing a standard SC process reference model which can provide effective communication among the supply chain partners, by

- Using standardization in terminology that provides better communication.
- Using standardization in metrics to measure and compare their performances.

SCOR helps to integrate Process Measurement, Benchmarking and Business Process Reengineering in a framework (Balocco et al., 2011). SCOR is also effective in describing, measuring and evaluating supply chain configurations. It provides:

- Conceptualized framework for relationships among the standard processes.
- Standardized metrics to measure performance.
- Management practices that can produce performance.

- The standard practices for management processes.

SCOR spans:

- All the market interactions, from understanding of the aggregate demand to the fulfillment of each order.
- All the customer interactions, from order entry through paid invoice.
- All the transactions from supplier's supplier to customer's customer, including supplies, equipment, bulk product, software, spare parts etc.

SCOR does not describe each and every business process like research and technology development, product development, sales and marketing, and some elements of post-delivery customer support (Blackhurst, Scheibe and Johnson,. 2008). SCOR continues to evolve after it was developed. Industry leaders use it daily to analyze and improve the performance of their organization. It presents a very broad perspective and definitions that can be used for specific supply chain requirements of any industry or application (Lambert, Cooper and Pagh, Shibin, et al., 2016). SCOR has five primary SC attributes: Responsiveness, Reliability, Agilty, Asset Management and Costs. The SCOR can help to identify the risk elements which can occur in the supply chain of a firm. A metric is defined to analyze the impact of these risks and thus can help firms to control the severity and mitigate the disruptions (McCormacket al., 2008). External measure of supply chain responsiveness is capacity flexibility (Teichmail & Claus, 2017).

There are two types of performance attributes in the SCOR model. Responsiveness, reliability and flexibility come into customer facing performance attributes. Assets and cost come into internal-facing attributes. Following are the performance metrics under the category of performance attributes.

On Time and In Full : The delivery is on time with complete invoice.

Perfect order Fulfillment: It includes on time and in full along with other components which make it a perfect match which include perfect invoice and perfect receipt.

Order Fulfillment Lead Time: It is defined as the amount of time from the time when customer authorizes a sales order to the customer receives the product.

Supply Chain Response Time: It is defined as the amount of time it takes in which a supply chain can respond to an unplanned 20% increase or decrease in demand without any penalty in cost or service.

Total Supply Chain Management Cost: It is defined as the operational and operational costs associated with the Plan, Source, Make and Deliver SC processes.

Total Returns Management - Warranty Cost: It includes the cost associated with planned and unplanned returns of maintenance, defective .

COGS: It includes all the cost of the inventory used in making the goods and the direct labor costs used to make the goods. It does not include the indirect costs such as sales and distribution cost.

Return on Assets: Return on assets (ROA) indicates profitability of a company relative to its total assets. ROA can tell us how efficient a company's management is at using its assets to generate earnings.

Cash-to-Cash Cycle Time: It is calculated by adding the number of days of receivables outstanding to the number of days of inventory and then subtracting the number of days of payables outstanding.

Research Methodology

This study focuses at developing a Bayesian network for analyzing the various SCOR metrics within a supply chain. A thorough SCOR model review has led us to identification of various SC performance metrics. These metrics have to be incorporated in a model establishing relationship between them. Subsection 3.1 provides a brief description of Bayesian Networks.

Bayesian Networks

For the last few years, Bayesian Networks (BNs) have become an effective and popular tool for modeling of various statistical problems. BNs are quite effective in modeling complex and uncertain domains such as ecosystems and environmental management. BNs are helpful in summing the subjective beliefs with the available evidences (Chin, Tang, and Yang, 2009). A BN is a directed acyclic graph that establishes the probabilistic relationships among the nodes of interest in a problem. The representation of structural model describes the probabilistic relationships and has a model that facilitates the communication between the user and a system (Cowell, Verrall, and Yoon, 2007). Bayesian network foundation is derived from the work of the theologian and mathematician Rev. Thomas Bayes who came with the concept of conditional probability theory in the late 1700s to derive a basic law of probability which later on came to be known as Bayes theorem. There are three main inference tasks for Bayesian networks.

A BN for a set of variables say U = {Y1,. . . ,Yn} is a pair, BN = (Gr, H) where Gr represents the directed acyclic graph and H tells about the parameters with which we quantify the network. The variables make the vertices and the child - parent relationship between these variables forms the edges. If an edge is there from Yi to Yj, then Yi is called the parent of Yj and Yj is called the child of Yi. A node without any parent node is called the root node and a node which had no child node is a leaf node or we can also say an outcome node. It is very important to note there is no difference between a variable and a node in BN, and these nodes can be continuous or discrete. Each node contains one of its states for a discrete variable which might not be known to the decision maker. State is nothing but explains all the possible values that a variable might take. A variable Yi and its parent, parent(Yi), tells the conditional probability distribution, P(Yi|parent(Yi)). Conditional probability table for a set of variables is formed by this. The more are the number of states of a parent node the more is the complexity of the CPT. BN can be used to understand how the change in the probability of one variable changes the probability of others. If the joint probability function of the variables are known, P(U) = P(Y1, . . . , Yn), we can find the answer to this question by finding the marginal distribution of a variable, P(Yi), or finding the conditional distribution of Yi provided we the evidence, e, P(Yi|e).

Evidence is nothing but simply means that the variables are observed and their values come from their respective domains. Calculating P(U) for a large network is quite complex as P(U) grows exponentially as the number of nodes are increased. The BNs are extremely helpful as the importance of BNs lies in the fact that by using Bayes theorem, we can not only find just the probability of child if we are given the values of the parent nodes, but if the probability of the children are given we can find the probability of the parents. Bayes' theorem states that:

BNs can be applied both ways like: Top Down, that is it can be used as a predictive modeling and Bottom Up, that is it can be used for diagnosis. Thus, we can not only find the consequences given the causes, but can also get the probabilities of various causes given the consequences.

One of the most important features of BNs is that we can facilitate flexible results with partial information (Zeng and Sycara, 1998). Correspondingly, the concept of BNs has become very popular in areas of medical diagnosis, safety science and weapon tracking systems.

Parameter learning

We need to specify the probability distribution for each node X conditional upon X's parents in order to fully specify the BN. Since the distribution of X conditional upon its parents may take any form. It might help to use Gaussian distribution or discrete distribution since it may simplify calculations. One can use the principle of maximum entropy to determine a single distribution in case only constraints on a distribution are known, the one with the greatest entropy given the constraints. We can estimate the parameters using the maximum likelihood approach of conditional distributions which are sometimes unknown. It becomes very complex to directly maximize the likelihood if there are unobserved variables. We can solve this problem by using the expectation-maximization algorithm which alternates computing expected values of the unobserved variables conditional on observed data, with maximizing the complete likelihood (or posterior) assuming that previously computed expected values are correct. Under mild regularity conditions this process converges on maximum likelihood values for parameters.

Structure learning

Machine learning can help to automatically generate the graph. Rebane and Pearl (1987) gave the basic idea of recovery algorithm. The complete idea depends on the difference between the three types of adjoining triplets possible in a DAG:

1. $X \rightarrow Y \rightarrow Z$
2. $X \leftarrow Y \rightarrow Z$
3. $X \rightarrow Y \leftarrow Z$

1 and type 2 shows the same dependencies (If is given X and Z are independent). However, 3 is different and we can be uniquely identify it as and are independent to some extent and all other pairs are dependent. So, even when structure of these triplets are same, the direction of the arrows can be partially identified. The same difference can be applies when and common parents but we must first condition on the parents. There are algorithms which we can us to develop skeleton of the graph and can thus can change the orientation of all arrows whose directionality is dictated by the conditional independencies observed.

There is yet another method in which we focus on the sub-class of decomposable models to get the structure, for which the MLE have a closed form. This method is very helpful using which we can to develop a consistent structure for a large number of variables.

We can make a BN with the help of rule-based machine learning . New rules can be generated and new nodes can be created using Inductive logic programming. Statistical relational learning (SRL) approaches use a scoring function based on the Bayes network structure to guide the structural search and augment the network.

Bayesian Belief Network modeling steps

The following diagram represents the methodological steps used in this study.

Implementation of Bayesian belief networks (BBN) modeling requires factor identification and then establishing relationship between them. The first step in the BN modelling is the development of the Structure and its Evaluation on the first iteration it will give an unparameterised causal

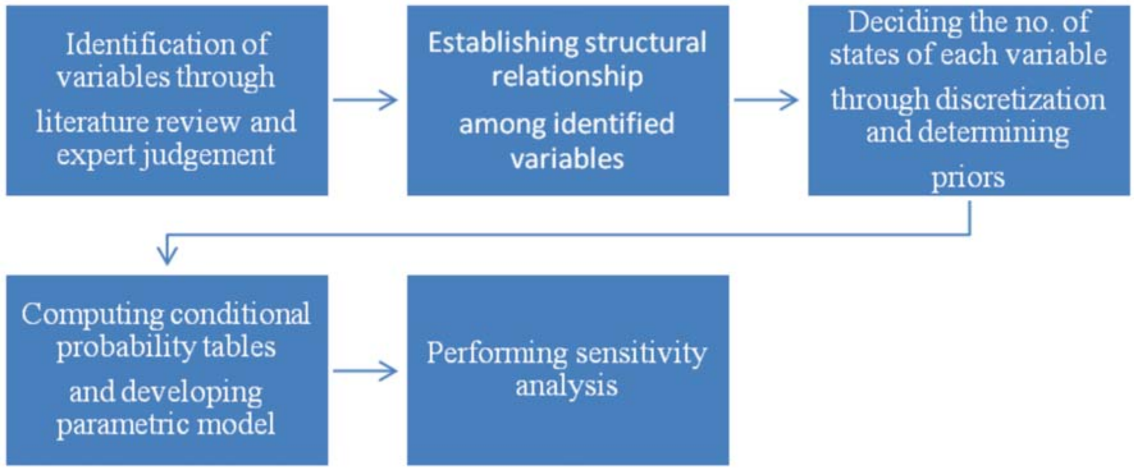

Fig. 1 Steps in Bayesian Belief Network (BBN) Model

network. This model development can be done using knowledge or data-based approach. Knowledge based model development is done through expert elicitation of parameters. The factors were identified using literature review and then prepared list was sent to experts for validation. Once relevant variables were identified, and then experts were asked to draw linkages among various risk factors, used in the study.

For establishing structural relationship among variables, Delphi method was used. Once, opinions of experts converged on a particular structure that was taken for further evaluation. The experts were supply chain managers. In step 3, before parameterization, discretize all the variables into states. In case of continuous variables, states are to be further discretized into sub-ranges. Wherever possible, states were established using guidelines, management threshold or recognized classifications. When, the guidelines were not present, sub-ranges were made with proper guidance of experts. We did not pre-determine the number of 'states' assigned to each node, but it was evaluated and assigned on an individual basis. In step 4, expert opinion is applied on conditional probability tables, rather than individual parameters. For parent variables, priors were drawn out and for child nodes; CPT was drawn out for each and every possible state for a child variable.

In the final step, Sensitivity analysis is used to find the changes in probabilities of output variables when inputs and parameters are changed. Two types of sensitivity analyses were used in evaluating the BBN. The first is, "sensitivity to findings", it is how BN's posterior probabilities change under different conditions and the second is, "sensitivity to parameters", it is how the BN's posterior probabilities change when parameters are changed. In the next section a brief overview of BBN modeling has been provided.

Research Model

This research study employs a BBN model for quantifying the impact of variables in SCOR on firm's revenue. The model consists of the already described variables of the SCOR metrics. Model shows the relationship between SCOR variables and the firm's revenue. Each node represents an independent variable and direction of the arrow signifies the relationship between them. The following diagram showing structural relationship that is known as influence diagram.

Data Collection

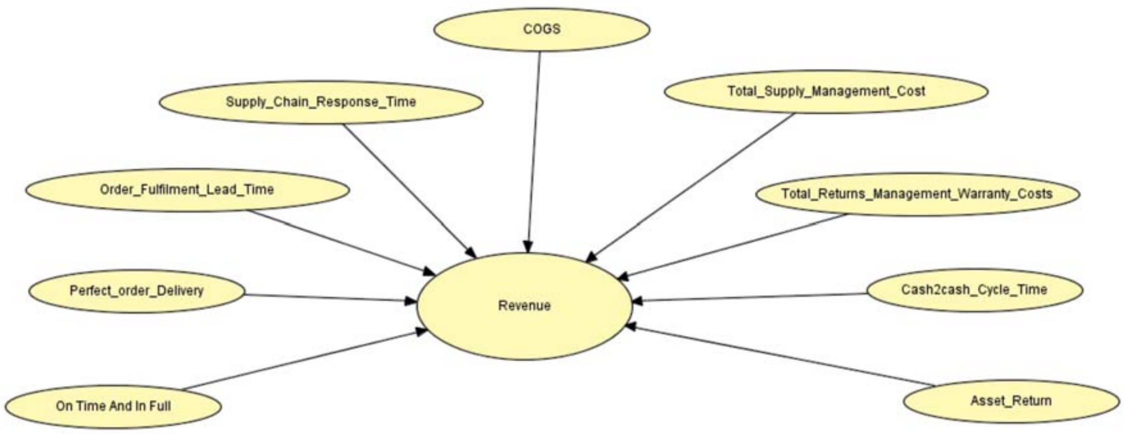

Fig. 2 : The Proposed Framework for Bayesian Network

In model structure given in Fig. 2, consideration was only given to the relationship between parent nodes and child nodes. This structure was created in consultation with subject matter experts (SME) and it is ensured that the proposed structure is the one. Next step is to draw out the past data and expert knowledge into conditional statements and probabilities.

The data sample consists of five major automobile manufacturers in India and abroad. These five companies are very large in automotive sector operating in India and abroad. The selected companies are very large and their turnover is more than 5000 cores and employee size is greater than 2000. The data collected is between the time periods of 2006-2015.

Data Analysis

Table 1 Threshold Values of Performance Indicators

SCOR Variable	Measurement Scale
On Time and In Full	• High > 79 % • Low <= 79%
Perfect Order Delivery	• High > 59% • Low <= 59%
Order Fulfillment Lead Time	• High > 28 Days • Low <= 28 Days
Supply Chain Response Time	• High > 122 Days • Low <= 122 Days
COGS	• High > 85% of Revenue • Low <= 85% of Revenue
Total Supply Chain Management Cost	• High > 14.5% of Revenue • Low <= 14.2 of Revenue
Total Return Management Warranty Cost	• High > 2.4 % of Revenue • Low <= 2.4 % of Revenue
Cash to Cash Cycle Time	• High > 130 Days • Low <= 130 Days
Asset Returns	• High > 0.10 • Low <= 0.10

The Bayesian network deals with the various variables involved in a SCOR metrics. The Bayesian network was tested for a set of data obtained for various input nodes assigning normal distribution to the rest. The BN was modeled using Hugin Lite 8.3 software. Fig. 3 shows the distributions and results obtained after simulating the model using input data for Fiat Chrysler Automobiles.

Thus, the model examines the probability of impact on company's revenue based up the firm's

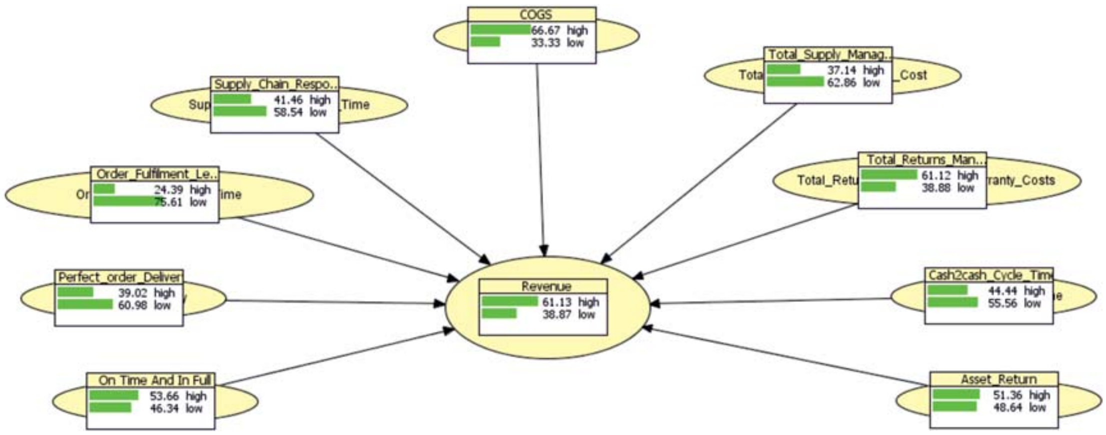

Fig. 3 The Results of the Simulation of Fiat Chrysler Done Using Hugin Lite

SCOR metrics. These prior probabilities of parent nodes were assigned using the data. Bayesian Networks can not only be used to model risk and find the impact on revenues but can also be used on a more backward approach (bottom to top) to diagnose the possible causes of variation in profitability due to information supply chain risk factors. When we know a variable's real state out of possible states in the model, we can study its impact on distributions on other modes as well.

As Fig. 4 provides the backward reasoning when provided with data such as to get high revenue, probability of Asset return is significantly increased by 9 percent as well as we see that the factors like on time and in full, perfect order delivery order fulfillment lead time, supply chain response and COGS impact on revenue is there but its low its effect is inverse which is quite intuitive. Thus it is evident that the impact on revenue is from asset return and is quite obvious which is evident from the results obtained as shown in the Fig. 4.

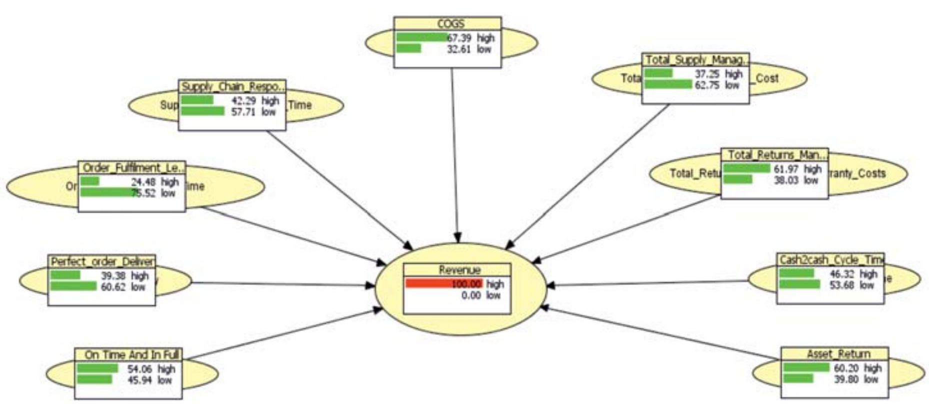

Fig. 4: Analysis of Risk Factors when results are known for Fiat Chrysler.

Table 2: Sensitivity Analysis on individual Factors for Fiat Chrysler

Factor	Change (%)	Effect on Revenue (%)
On Time and In Full	46.34	0.46 (positive)
Perfect Order Delivery	60.98	0.56 (positive)
Order Fulfillment Lead Time	75.61	0.23(positive)
Supply Chain Response Time	58.54	1.21(positive)
COGS	33.33	0.66(positive)
Total Supply Chain Management Cost	62.86	0.17(positive)
Total Return Management Warranty Cost	38.88	0.86(positive)
Cash to Cash Cycle Time	55.56	1.58 (positive)
Asset Return	48.64	10.53 (positive)

For the above case the Order Fulfillment Lead Time and Total Supply Chain Management Cost plays significant role.

Tata Motors

Fig. 5 Shows the Distributions and Results obtained after simulating the model using input data for Tata Motors.

As Fig. 6 provides the backward reasoning when provided with data such as to get high revenue,

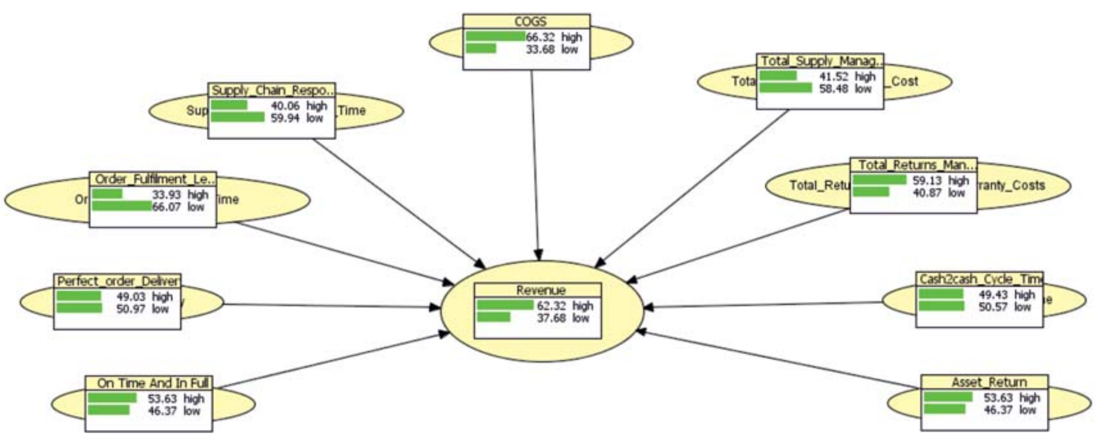

Fig. 5 The Results of the Simulation of Tata Motors Done Using Hugin Lite

probability of Asset return is significantly increased by 8 percent as well as we see that the factors like on time and in full, perfect order delivery order fulfillment lead time, supply chain response and COGS impact on revenue is there but its low and its effect is inverse which is quite intuitive. We observe that the results obtained for Tata Motors is quite similar to what we saw for Fiat.

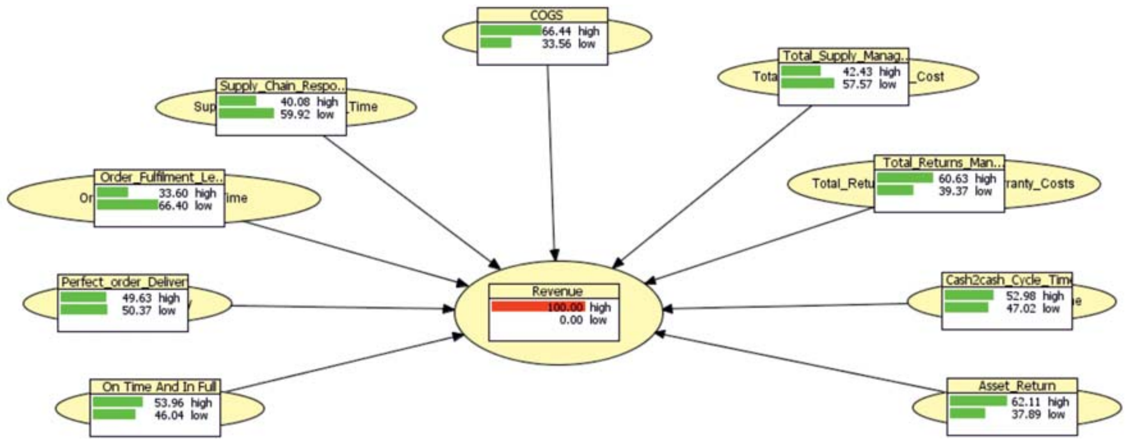

Fig. 6 : Analysis of Risk Factors when results are known for Tata Motors.

Table 3 : Sensitivity Analysis on individual Factors for Tata Motors

Factor	Change (%)	Effect on Revenue (%)
On Time and In Full	46.37	0.38 (positive)
Perfect Order Delivery	51.97	0.76 (positive)
Order Fulfillment Lead Time	66.07	0.59(negative)
Supply Chain Response Time	59.94	0.03(positive)
COGS	33.68	0.12(positive)
Total Supply Chain Management Cost	58.48	1.36(positive)
Total Return Management Warranty Cost	40.87	1.59(positive)
Cash to Cash Cycle Time	50.57	4.47 (positive)
Asset Return	46.37	9.85 (positive)

For the Tata motors case the Order Fulfillment Lead Time and Total Supply Chain Management Cost plays significant role.

Maruti

Fig. 7 : Shows the Distributions and Results Obtained after Simulating the Model using Input Data

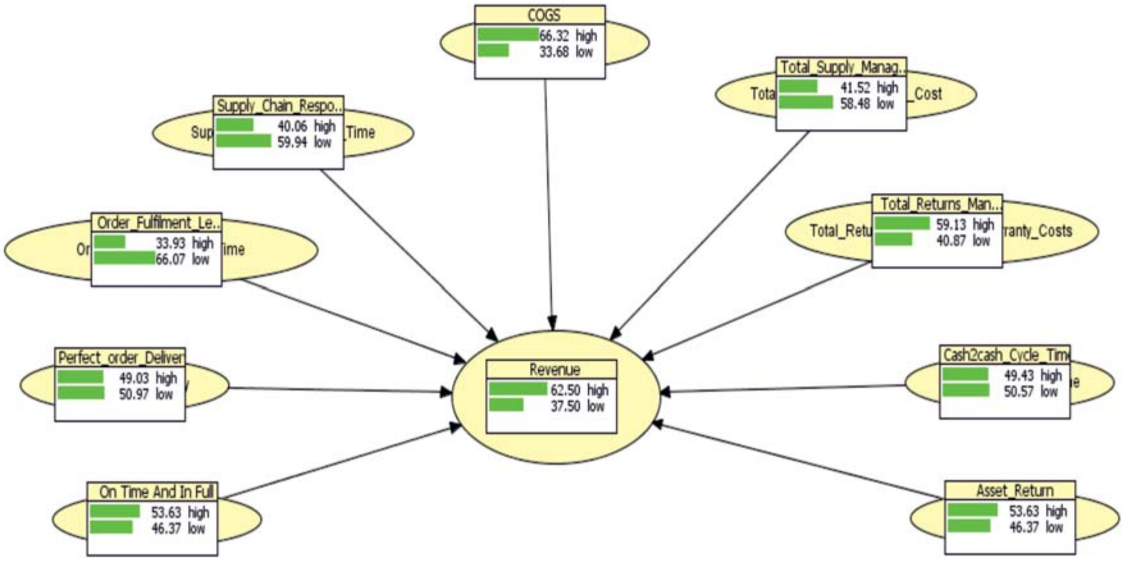

Figure 7 : The Results of the simulation of Maruti done using Hugin Lite

As Fig. 8 provides the backward reasoning when provided with data such as to get high revenue, probability of Asset return is significantly increased by 8 percent as well as we see that the factors like on time and in full, perfect order delivery order fulfillment lead time, supply chain response and COGS impact on revenue is there but its low and its effect is inverse which is quite intuitive. We observe that the results obtained for Tata Motors is quite similar to what we saw for Fiat and Tata Motors.

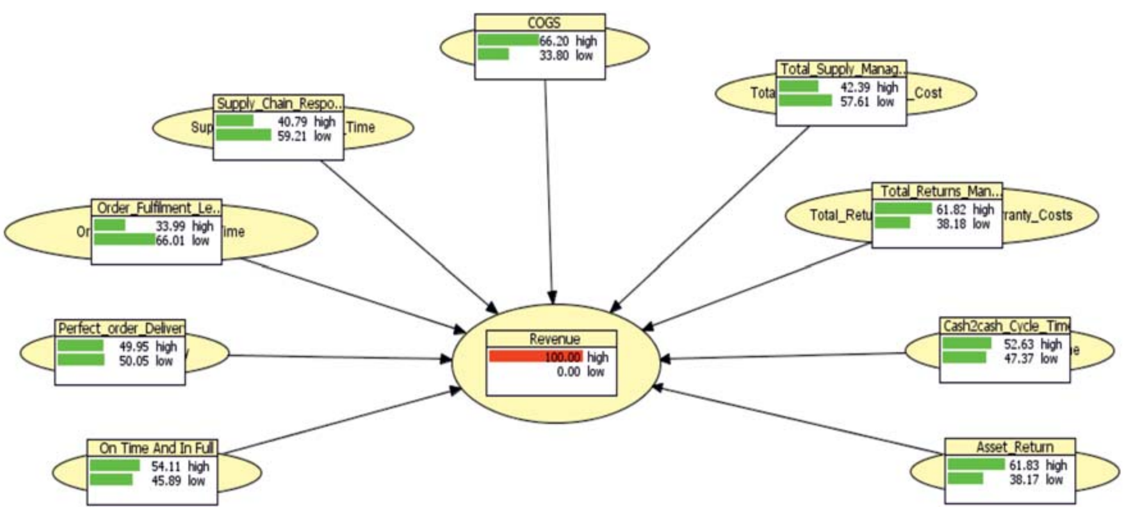

Fig. 8 : Analysis of Risk Factors when results are known for Maruti

Table 5 Sensitivity Analysis on individual Factors for Maruti

Factor	Change (%)	Effect on Revenue (%)
On Time and In Full	46.37	0.53 (positive)
Perfect Order Delivery	50.97	1.17 (positive)
Order Fulfillment Lead Time	66.07	0.11(positive)
Supply Chain Response Time	59.94	1.13(positive)
COGS	33.68	0.11(negative)
Total Supply Chain Management Cost	58.48	1.31(positive)
Total Return Management Warranty Cost	40.87	2.84(positive)
Cash to Cash Cycle Time	50.57	4.03 (positive)
Asset Return	46.37	9.55 (positive)

For the Maruti case the Order Fulfillment Lead Time and Total Supply Chain Management Cost plays significant role.

Managerial and theoretical Implication

In this research paper an SCOR metrics model has been developed using BBN. In Bayesian models, reasoning can be done in both ways. The variables in the SCOR metrics affect the revenue. The managers can study the impact using BBN. For some of the factors whose data is not readily available, their probability can be obtained from subjective data (expert's judgment). Managers can use Propagation analysis using BBN to update the probability, when new data comes. In risk analysis, probability updating is the task of calculating all the posterior marginal of non-evident variables given the evidence. Sensitivity analysis explains the importance of various variables on the SCOR metrics. We can diagnose the responsible factors using Bottom Up analysis of BBN. Results of Sensitivity analysis show that 'Return On Assets' is the most important factor along with marginal impact of Delivery Performance. As now managers know the role of individual factors they can take possible initiatives to bring about possible positive effects in revenue. As the most impactful factor is return on assets and also its quite intuitive that return on asset do affect the revenue largely. We also see here that for delivery performance also do have positive and marginal impact on revenue. The managers need to see to it that how can they improve on these factors and hence can increase the revenue.

The proposed Bayesian model very well shows the evidence based practice. The Bayesian modeling can is highly useful in test hypotheses and theories. BBN tests theories based on new evidences. This research can also help in giving directions to researchers, who want to use BBN modeling in future. This paper presents a complete practical approach for structural and parametric learning. This methodology also helps to update the posterior probabilities when new evidences come.

Limitations

The study was conducted in automobile industry; therefore, the results might be industry-specific in nature. In addition, the study examined only 3 companies in the automotive industry, thus limiting the generalizability of variables of SCOR metrics in this sector. One limitation here may be the use of the BN methodology is the ability to access the necessary data needed to construct the Bayesian networks.

Conclusion and future scope of research

In this paper, we have proposed an assessment model for the impact of variables in the SCOR metrics on the revenue of a firm risk using Bayesian Networks. As we already discussed the capability of Bayesian networks while we model it in uncertain conditions, this helps in providing the perfect platform for analyzing the models providing a very robust method for studying the impact of various factors. The data analysis in above section shows results obtained for a study on automobile companies and the changes observed in the values of probabilities when certain data sets are known with full certainty. If the probability distribution can be made more reliable and accurate if filed and more accurate data is provided to us. One of the best features of the Bayesian Network is that we can ability to incorporate new data to change probability distribution. Hence, we can improve the predictions made in the study if we are provided with more reliable data, which is a limitation for the project. Study of SCOR metrics factors for companies and supply networks in other industries can be examined using the methodology illustrated in this study.

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