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Performance Prediction of Green Supply Chain Using Bayesian Belief Network: Case Study of a Textile Industry

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Abstract

In managing a supply chain, the green approach has become pivotal for the sake of environmental, economic, and social sustainability. In this paper, we consider the environmental performance prediction in managing sourcing of a textile industry supply chain. Specifically, this research focuses on the dying sector of an emerging economy. We identify eleven green supply chain performance indicators and four performance measures and perform both qualitative and quantitative analyses. The performance is predicted using a probabilistic model based on a Bayesian Belief Network (BBN). The robustness of the findings is validated through a sensitivity analysis. The outcomes suggest that 'Total Suspended Solids' (TSS) and 'Volatile Organic Compounds' (VOC) are the most important indicators for the case company in this study with the highest entropy reduction. Also, 'air emission' was found to be the most impactful performance measure for entropy reduction. This research work will help improve the decision-making capability of the managers and practitioners considering the total environmental performance of the green supply chain. The improved decision-making will also improve overall organizational performance of a green supply chain.

Keywords: Green supply chain, Sustainability, Bayesian, Performance prediction, Textile industry.

1 | Introduction

Bangladesh is one of the largest export trading countries for Readymade Garments (RMG) and apparel in the world. For many years, textile industry has long been the lifeblood of the Bangladesh's economy [15]. Bangladesh's RMG export has significantly over the last few years (*Fig. 1*) and contributed heavily on the nation's GDP. However, textile manufacturing processes have long been chastised for contributing to detrimental environmental activities such as excessive non-renewable resource waste and global warming and other severe poisonous chemicals, as well as global warming materials. These procedures and the usage of numerous chemicals not only generate environmental concerns, but they also cause greenhouse gas emissions, water and resource depletion, acidification, and a variety of health issues.

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The UN's 12th sustainable development goal strives for "responsible consumption and production" with objectives including effective use of natural resources, ecologically sound chemical and waste management, improved technological integration, and knowledge distribution about these practices. The manufacture of textiles, which is resource-intensive owing to the procedures of washing, dyeing, and finishing, is the largest problem for the RMG industry [20].

The Green Supply Chain Management Process (GSCMP), which addresses environmental safety at every stage of the process, is seen to be an effective way to reduce the negative environmental consequences of textile manufacturing [2]. Furthermore, implementing GSCMP can assist textile firms in saving a significant amount of operating energy, lowering costs, increasing efficiency, and reducing the quantity of hazardous waste generated [19], [25]. Again, adopting GSCMP is a requirement for asserting greater commercial prospects and gaining a strong market position by generating a sense of excellent brand image among customers [31]. Because of growing competitive, regulatory, and societal demands, companies are now attempting to include environmental performance into the evaluation of total supply chain performance [12], [33].

Companies must create and implement plans to reduce the environmental effects of their products and services in a supply chain [36], [41]. The fundamental ideas on which a company's business is founded can be examined and revised for the firm to present a green image. Furthermore, addressing environmental concerns is critical for a firm to establish a distinctive competitive advantage and increase the value of its main business activities [28], [30], [32]. According to Alzubi and Akkerman [7], poor environmental awareness reduces stakeholders' concerns to improve their sustainable SCM. Market expectations, risk management, regulatory compliance, and company efficiency are some of the components that establish a competitive advantage via environmental performance, according to the Confederation of British Industries in 1994. Researchers and practitioners utilize Green Supply Chain Management (GSCM) as an effective method to handle all these components correctly [21]. As a result, GSCM allows a firm to grow profit and market share while simultaneously increasing its ecological efficiency [27]. GSCM aims at achieving three sustainability pillars – economic, environmental, and social [4], [22].

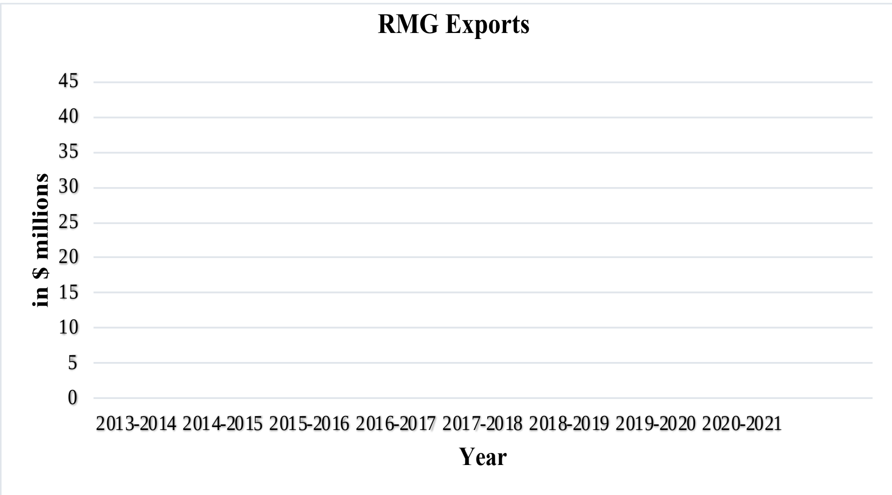

Fig. 1. Bangladesh's RMG exports (2013-2021) [9].

Bangladesh's typical textile factory utilizes 300 liters of water per day, putting substantial strain on the country's freshwater supplies considering the scale of the industry (DATABD.CO). *Fig. 2* depicts how environmental effects are divided across the various phases of the manufacturing process on average, with the raw material extraction and input production processes being the most concentrated. Because of growing public awareness and government restrictions, the textile sector is under pressure to develop environmentally friendly supply chain procedures. Manufacturers usually incorporate those components in such environmentally friendly procedures that have the least detrimental influence on human health and the environment throughout the manufacturing, use, conservation, and disposal of textile goods.

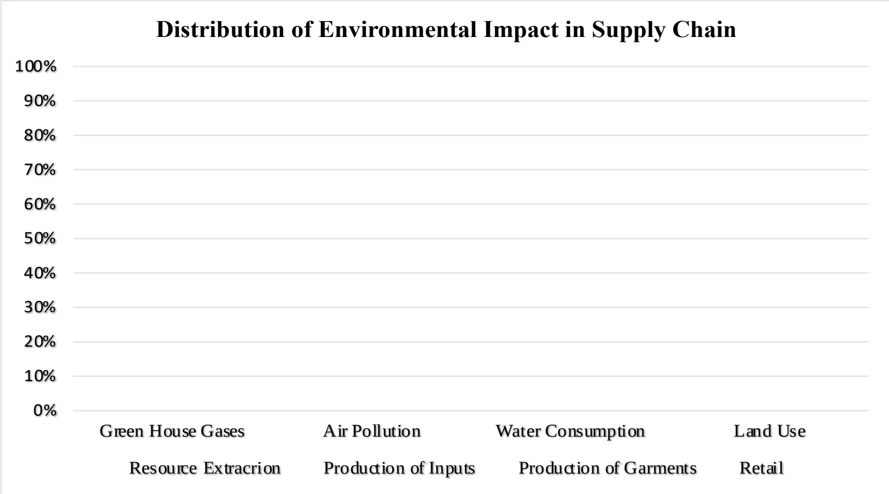

Fig. 2. Distribution of environmental impact in RMG supply chain [34].

As some of the cases raw materials are affected on the environment so it is important that to identify which raw materials affect rapidly our environment and which are also green raw materials for textile industry [3], [16]. GSCMP is critical for recognizing certain types of raw materials. Because of recent advancements in the field of GSCM, its performance prediction is gaining attraction [6], [11]. Although various metrics for measuring supply chain performance have been proposed, they do not cover all components of the green supply chain. As a result, more comprehensive environmental performance indicators are required. The goal of this research is to discover these performance indicators and utilize them to forecast the success of green supply chains in various circumstances. There have been several studies on traditional supply chain performance assessment, but only a handful have focused on the supply chain's environmental performance. As a result, none of the available research focuses on creating and applying probabilistic and quantitative approaches to forecast the performance of green supply chains.

This research aims to answer the aforementioned research issues by establishing GSCM performance metrics through a review of the current literature and expert opinion, as well as constructing a quantitative and probabilistic model utilizing a Bayesian Belief Network (BBN). A real-world case study of a textile industry is used to show the model's efficacy, as well as sensitivity and diagnostic studies to assess the influence of various indicators on overall performance. By BBN model identifying the indicators were identified which materials are green and non-green. Those raw materials which are non-green but is needed for textile industry we suggested to use alternative raw material/ by recycling those raw materials.

2 | Literature Review

GSCM is defined as "the process of transforming environmentally friendly inputs into outputs that can be reclaimed and re-used at the end". Consumers will ask more questions about the products they buy as they become more aware of environmental issues and global warming. Companies must prepare to answer questions about how environmentally friendly their manufacturing processes are [14]. GSCM integrates environmental thinking into supply-chain management which includes product design, material sourcing and selection, manufacturing, processes, final product delivery to consumers, and product end-of-life management after its useful life [40].

Sustainable development has made significant progress toward establishing environmental and social sustainability. Sustainability is comprised of three components: economic, environmental, and social. GSCM is concerned with making the entire supply chain more efficient and environmentally friendly. GSCM can be used for a variety of purposes, such as being required by law and regulations, differentiating oneself in a competitive industry by being environmentally friendly, and finally, implementing GSCM to remain competitive if your competitors have already adopted GSCM. Organizations with greener supply chain management practices will have a competitive advantage over companies that are hesitant to embrace

GSCM as customer awareness and regulatory norms rise [39]. As a result, there is a shift in the industry's focus on GSCM creating value for customers and shareholders [14], [38].

Most respondents proved that their textile organizations had embraced a redesigned supply chain system to decrease carbon footprint, streamline transportation operations to decrease carbon footprint, eliminate, reduce, and alternately repurpose manufacturing waste, and increase utilization of renewable vitality sources as well as eliminate/lessen hazardous/toxic materials. Employee's values were the highest influencing element influencing company choice for usage for GSCM taken after promises by the top administration [2]. It is important for RMG sector to apply green activities in their supply chain system to effectively use resource and save the nature from uncertain pollution which leads to sustainable business and eco-friendly world. Factors in material, manufacturing, recovery procedure [18].

In these papers listed in *Table 1*, authors depict the supply chain management in textile industry, gave recommendation showing the ways to reduce the waste, importance of implementing GSCM, performance measures if this was implemented in various industries. In our paper, we adopt the research framework developed by Rabbi et al. [35] who performed GSCM performance prediction analysis for a manufacturing industry. We conduct this study for a textile industry.

Table 1. Summary of the literatures studied.

Source	Approacg Used	Reaserch Contribution
Rabbi et al. [35]	BBN	Analyzed various green supply chain performance measures and indicators.
Ahmed et al. [2]	Information was sourced from 200 respondents.	The majority of respondents proved that their textile organizations had embraced a redesigned supply chain system.
Gomes and Daud [18]	Information and data has collected through several interview.	Proper use of the raw materials in their roductionprocess to minimize the waste of resources due to limited of natural resource.
Ali and Habib [5]	The analisis of this research is based on secondary data.	Developed a customized supply chain model for the textile sector in Bangladesh.
Farhan Shahriar et al. [15]	Secondary data were collected from various publications.	Bangladesh garment industry improvement is desired in reducing the supply time required to produce and fulfill the orders placed by foreign companies.
Akter and Uddin [3]	Primary and secondary data	Different areasof apparel industry and provided recommendation for these areas.
Dey and Islam [13]	A standard method for sampling	The samples were analyzed for various physicochemical parameters. They have given a solution to use ETP.
Mia et al. [29]	Based on secondary data	Showed ways of preventing pollution in different factories of Bangladesh.
Hossain and Roy [23]	The study is mainly based on secondary data and merely on primary data.	Importance of supply chain in the growth of MRG Industry, problems toward sustainable RMG growth and provide recommendation.

3 | Research Methodology

The goal of this research is to find out the performance measures and indicators that are harmful for our environment. This research is focused on Bangladesh textile industry's dyeing sector. The four-step research framework used in our paper is shown in *Fig. 3*.

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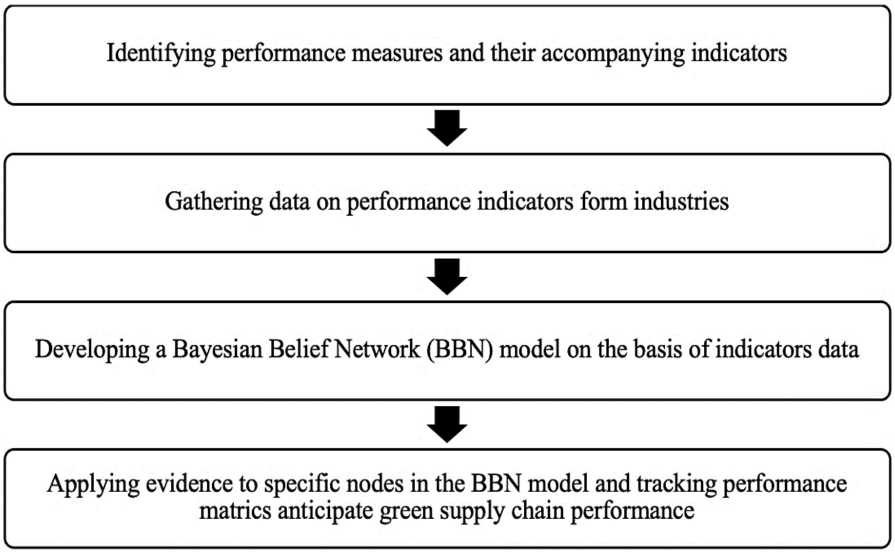

Fig. 3. Research framework of this study [35].

Step 1. Identifying performance measures and their accompanying indicators: in this step, we identified some indicators with their corresponding measures that were relatable with green supply chain performance. All the indicators were identified by reviewing some literature review and papers. For green performance indicators, researchers looked at papers on green purchasing, green consumption, green marketing, green manufacturing, green 3R (reduce, reuse, recycle), and supply chain performance evaluation.

Step 2. Gathering data on performance indicators form industries: in this step, we gathered data about selected indicators from industries. Among these data which were more acceptable we selected them for next step.

Step 3. Developing a BBN model based on indicators data: in this step, we developed a BBN model regarding the selected data. Here we used two hypothesis states (satisfactory state and unsatisfactory state) for calculating performance level.

Step 4. Applying evidence to specific nodes in the BBN model and tracking performance metrics anticipate green supply chain performance: in this step, we applied some analysis to validate the BBN model so that we could be sure that our outcome is right, and, in this way, we can find which performance measures (*Fig. 4*) and indicators affect mostly our environment.

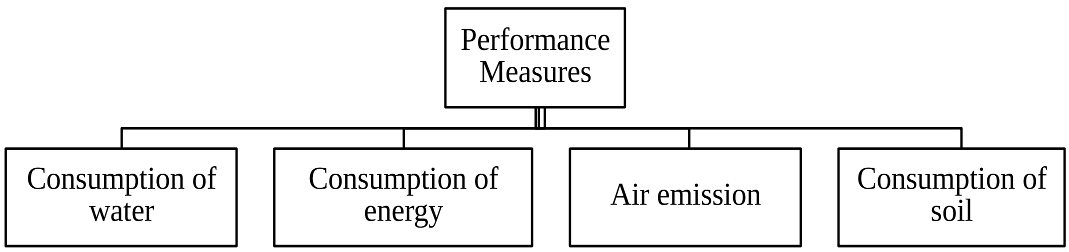

Fig. 4. Selected performance measures.

3.1 | Identifying Performance Measures and Their Corresponding Indicators

For identifying performance measures and their corresponding indicators we viewed some research papers in which the selected indicators used. Our environment is affected mostly by water pollution, air pollution, consumption of soil and energy. In our work, we took four types of performance measures as they affected our environment mostly. Under the four performance measures identified 11 indicators by reviewing papers. *Table 2* shows four performance measures with their corresponding indicators.

Table 2. Green supply chain performance measures and indicators.

Performance Indicators Measures	Indicators	References
Consumption of water	Biological Oxygen Demand (BOD)	[24], [29], [37]
	Chemical Oxygen Demand (COD)	[24], [29], [37]
	Total Suspended Solids (TSS)	[24], [37]
Consumption of energy	Total Dissolved Solids (TDS)	[24], [37]
	Potential of Hydrogen (PH)	[24], [37]
	Adsorbable Organic Halides (AOX)	[24], [37]
	Greenhouse gas emission	[24]
Air emission	Emission of CO_2	[24], [37]
	Smog	[24], [37]
	Volatile Organic Compounds (VOC)	[24], [37]
	Rate of toxic material	[24]
Consumption of soil		

3.1.1 | Consumption of water

For industrial operations, the dyeing and printing industries consume a lot of water. In terms of both volume and effluent composition, wastewater from the dyeing and printing industries has been identified as the most polluted water. Because of the ease with which raw materials and completed products can be transported, these are generally located along riverbanks. As a result, industrial effluent flows directly into the river, with no filtering or treatment of polluted water [29]. That's why we selected consumption of water as performance measures. BOD, COD, TDS, TSS, PH, AOX all of these are indicators which indicate the quality of water.

Biological Oxygen Demand (BOD): the BOD is a measure of the amount of oxygen required to break down organic materials in water. A higher BOD means that more oxygen is required, implying that the water quality is poor. Low BOD indicates that less oxygen is taken from water, implying that the water is usually purer.

Chemical Oxygen Demand (COD): the amount of dissolved oxygen that must be present in water to oxidize chemical organic compounds is known as COD. The presence of decaying plant debris, human waste, or industrial effluent is common in water with a high COD.

Total Suspended Solids (TSS): TSS are a water quality metric defined as the number of particles suspended in a known volume of water that can be trapped in a filter.

Total Dissolved Solids (TDS): TDS stands for total dissolved solids, which refers to the inorganic salts and small amounts of organic matter that are present in solution in water.

Potential of Hydrogen (PH): the PH of water is a measurement of how acidic or basic it is. The range is 0 to 14, with 7 being the neutral value. Acidity is indicated by a PH less than 7, while a PH greater than 7 indicates a base. PH is a measurement of the proportion of free hydrogen and hydroxyl ions in water.

Adsorbable Organic Halides (AOX): the organic halogen load at a sampling site, such as soil from a landfill, water, or sewage waste, is measured using AOX. The technique detects comparable halogens such as chlorine, bromine, and iodine, but does not detect fluorine in the sample.

All these indicators are the measurement indicators of water that is why this research selected these types of indicators for water consumption.

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3.1.2 | Consumption of energy

The textile sector is a big energy consumer with a low energy usage efficiency. Improved energy efficiency should be a top priority for textile plants, especially in times of high energy price volatility. Every textile plant has a variety of energy-efficiency opportunities, many of which are cost-effective but aren't implemented due to a lack of information or a high initial cost [37].

Greenhouse Gas Emission: we selected greenhouse gas emission as an indicator of consumption of energy. Every year, the textile sector emits 1.22 to 2.93 billion metric tons of Carbon Dioxide (CO_2) into the atmosphere. As a result, the life cycle of textiles (including laundry) is estimated to account for 6.7 percent of all worldwide greenhouse gas emissions [10].

3.1.3 | Air emission

The textile industry's air pollution is also a key source of concern. Pollutants are emitted into the air by boilers, thermo packs, and diesel generators. Suspended Particulate Matter (SPM), sulphur dioxide gas, oxide of nitrogen gas, and other pollutants are produced. The emission of hazardous gas into the atmosphere has a negative impact on the human population in the surrounding areas. Reducing the toxins released by the textile sector has become vital.

Emission of CO_2: CO_2 emissions from burned fossil fuels are a major component to the greenhouse effect [37]. CO_2 is a colorless, non-poisonous gas that is produced by the burning of carbon and by the breathing of living beings. The release of greenhouse gases and/or their precursors into the atmosphere over a defined area and time is referred to as emissions.

Smog: Smog is a type of air pollution that was named from the combination of smoke and fog in the atmosphere. Smog is created by a mixture of smoke and sulfur dioxide and occurs when significant amounts of coal are burned in a certain area. Smog is a problem in many places and continues to be harmful to people's health. Seniors, children, and persons with heart and lung problems like emphysema, bronchitis, and asthma are especially vulnerable to ground-level ozone, sulfur dioxide, nitrogen dioxide, and carbon monoxide.

Volatile Organic Compounds (VOC): certain solids or liquids emit VOCs as gases. VOCs are a group of compounds that can have both short- and long-term health consequences. Many VOC concentrations are continuously greater (up to ten times higher) indoors than outdoors. Industrial solvents, such as trichloroethylene; fuel oxygenates, such as Methyl Tert-Butyl Ether (MTBE); or chlorination by-products, such as chloroform, are examples of VOCs. Petroleum fuels, hydraulic fluids, paint thinners, and dry-cleaning chemicals all contain VOCs. VOCs are typical pollutants found in groundwater. In textile industry there are used some materials which mainly polluted our air. By using these types of materials there are produced smog, CO_2. By this, our environment is polluted. By measuring smog quantity, CO_2 emission, VOC we can easily identify the air quality.

3.1.4 | Consumption of soil

There are many raw materials that cause soil pollution for textile industry.

Rate of Toxic Material: heavy metals are persistent by nature, and certain of them (such as cadmium, lead, and mercury) can bioaccumulate and/or be poisonous. Although they are found naturally in rocks, their usage by industry can release large amounts of them into the environment, causing ecosystem damage. Heavy metal complexes do not decompose into innocuous elements, although they can recombine to generate new ones [37]. Some types of material are involved in soil pollution. For this we consider the emission rate of toxic material which are mainly involved in this pollution.

3.2 | Data Collection

To develop a BBN model it is necessary to collect data from an industry. Based on the data, we can easily select that which indicator and performance measures mostly affect the environment. We collected six months data from the industry. We selected two states, one is satisfactory state and another one is unsatisfactory state for these data. All the indicators have standard value. When the data meet with the standard range then it will be satisfactory state. If not, then it will be in unsatisfactory state. Data table for the 11 indicators is given in *Table 3*.

Table 3. Data table for the 11 indicators.

Indicator (unit)	1st Month	2nd Month	3rd Month	4th Month	5th Month	6th Month	Recommended Limit
BOD (mg/L)	330	350	200	30	50	100	≤50
COD (mg/L)	100	150	200	700	750	800	≤200
TDS (mg/L)	1000	1500	3000	2700	2000	1300	≤2100
TSS	100	200	310	270	200	230	≤150
PH	7.5	9	10	11	8	9	6-9
AOX (mg/L)	0.87	1	7	5	9	6	≤5
Emission if CO_2 (tons)	512	100	200	2500	3000	2500	≤400
Smong (ppm)	1.9	2	7	5	9	6	≤2.5
VOC (kg)	0.5	400	310	450	500	320	≤0.750kg
GHG emission (tons)	0.87	1	7.5	5.7	9	6	≤4.6
Rate of toxic material (ppm)	200	60	70	200	250	180	≤100

Sample calculation for BOD: from the table data we can see that 4th and 5th month's data meet the satisfactory level. So, these two data will be in satisfactory state. The other data will be in unsatisfactory state:

I. Satisfactory state = 2/6*100% = 33.33%,
II. Unsatisfactory state = 4/6*100% = 66.67%,

We perform the same calculation for the other indicators and summarize the findings in *Table 4*.

Table 4. Anterior probabilities for green supply chain performance indicators.

Performance Indicators	State Probability (%) Satisfactory (s)	Unsatisfactory (u)
BOD	33.33	66.67
COD	50	50
TDS	66.67	33.33
TSSs	16.67	83.33
PH	66.67	33.33
AOX	33.33	66.67
Emission of CO_2	33.33	66.67
Smong	33.33	66.67
VOCs	16.67	83.33
Greenhouse gas emission	33.33	66.67
Rate of toxic material	33.33	66.67

3.3 | Bayesian Belief Network

A Bayesian Belief Network (BBN), or essentially "Bayesian Network," gives a straightforward method of applying Bayes Hypothesis to complex issues. Bayesian probability is the investigation of abstract probabilities or faith in a result, contrasted with the frequentist approach where probabilities depend simply on the previous event of the occasion.

A Bayesian Network is made of hubs and circular segments. Every hub addresses the arbitrary factors, and a variable can be discrete or persistent. Coordinated bolts or curves compare to the causal

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connection between the factors. These coordinated connections associate the pair of hubs in the graphical model.

In these connections, one hub straightforwardly influences the other hub, and in case there is no immediate connection, the factors are free of one another. A Bayesian Network has two parts: B = (G, θ). G is a directed acyclic graph with nodes and arcs in the first portion. The nodes represent the data set's variables $X_1, \ldots, X_n$, whereas the arcs represent direct dependencies between the variables. The independence relationships in the domain under research are then encoded in the graph G [8]. The conditional dependency distribution of is the second component of BBN, where $\theta_{(x_i|x_i)} = P_B(x_i \parallel x_i)$ is the set of direct parent variables of x_i in G [1]. The network B can be represented by using the joint probability distribution:

$$P_B\ X_1, X_2, \ldots \ldots \ldots X_N) = \prod_{i-1}^{n} P_B\ X_i|\pi X_i) = \prod_{i=1}^{n} X_i|\pi X_i).$$

Random variables are represented by nodes in a BBN, and probabilistic interdependence between the corresponding random variables are represented by edges connecting the nodes. Given the observation of complementary subset variables, a BBN is a probabilistic model that can compute the posterior probability distribution of any unobserved stochastic variable [17]. "Backward" probability propagation is also possible in a BBN, which is useful for determining the most likely scenario based on the evidence set.

4 | Results

4.1 | BBN Model Development

Netica software was used to create the BBN model. *Fig. 5* displays the prior probabilities of the states.

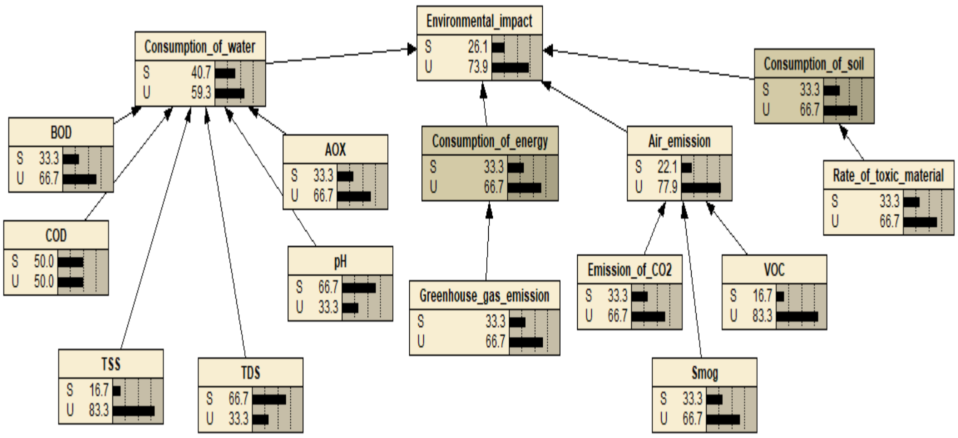

Fig. 5. BBN model for predicting green supply chain performance indicators.

From *Fig. 5* it can be found that the satisfactory state of "consumption of water" is 40.7% and unsatisfactory state is 59.3%, satisfactory state of "consumption of energy" is 33.3% and unsatisfactory state is 66.7%, satisfactory state of "air emission" is 22.1% and unsatisfactory state is 77.9% and satisfactory state of "consumption of soil" is 33.3% and unsatisfactory state is 6.7%. The outcome of this figure is the satisfactory state of "environmental impact" is 26.1% and unsatisfactory state is 73.9%. This outcome is based on current anterior probabilities of performance indicators that were calculated from industrial data.

4.2 | Model Confirmation

The suggested model was validated using both qualitative and quantitative confirmation methods [26]. For this, extreme-condition test and scenario analysis, and sensitivity analysis were performed, respectively.

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4.2.1 | Qualitative analysis

Qualitative analytics is used by businesses to examine circumstances where hard metrics are unavailable. In appraising a situation, quantitative analytics is objective and deductive, but qualitative analytics is subjective and inductive. Qualitative research is more abstract. This analysis was done with extreme – condition test and scenario analysis.

This research considers two extreme conditions to justify the model. In extreme – condition test we considered two cases. Case 1 is that when all the performance indicators are in good condition and case 2 is that when all the performance metrics are in a poor state of repair. *Fig. 6* and *Fig. 7* demonstrate the outcomes for extreme versions 1 and 2, respectively.

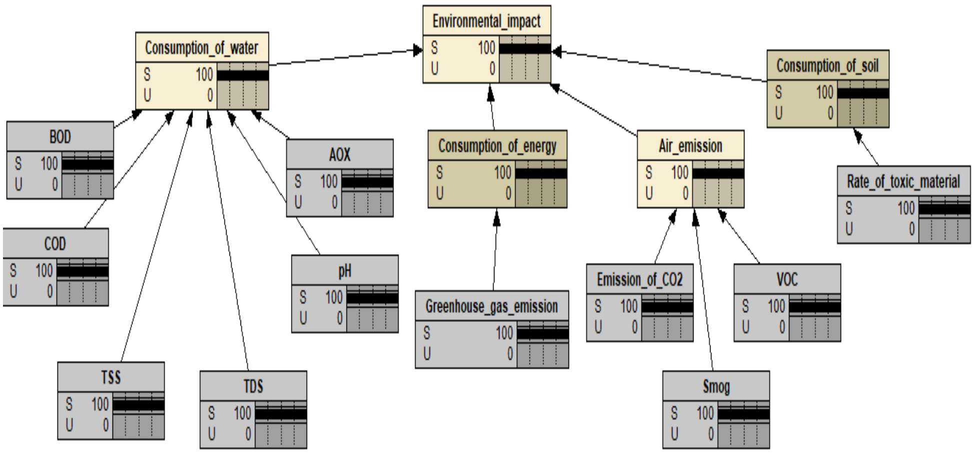

Fig. 6. Extreme case 1 when all performance indicators are in good condition.

Outcome: from extreme case 1, when all the performance indicators are satisfied, the environmental impact has a 100 % chance of being satisfactory. Again, from extreme case 2, when all the performance indicators have a 100% chance of being in an unsatisfactory state, the environmental impact has 0 percent chance of being satisfactory. As a result, the extreme – condition tests reveal that the suggested environmental performance model behaves as predicted.

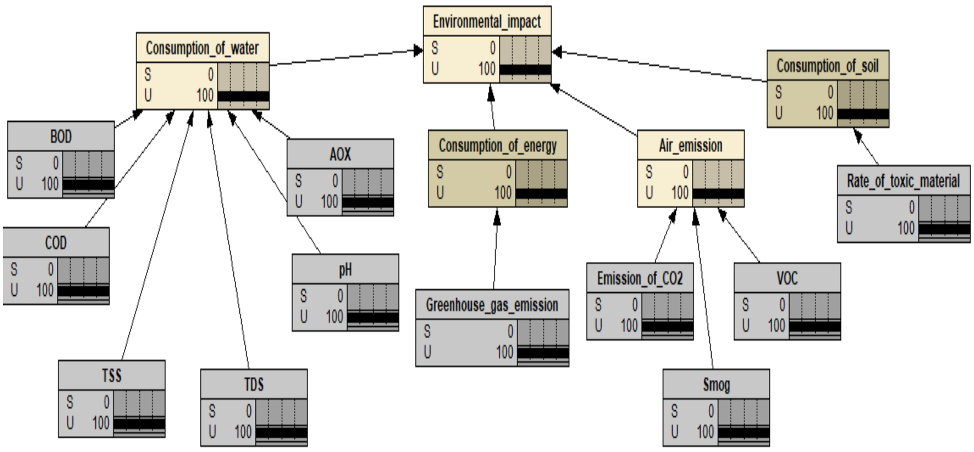

Fig. 7. Extreme case 2 when all the performance metrics are in a poor state of repair.

In this assessment, considered those indicators which have maximum level of unsatisfactory state that could be found from *Fig. 5*. Four performance indicators namely BOD, TSS, AOX, and VOC were considered for this assessment. Also, two performance measures namely "consumption of water" and "air emission" were considered for this analysis. Ten scenarios were considered for this assessment. In this analysis, all the satisfactory state were increased, and unsatisfactory state were decreased from the current values. The analysis' findings are depicted in *Fig. 8* to *Fig. 17* and displayed in *Table 5*.

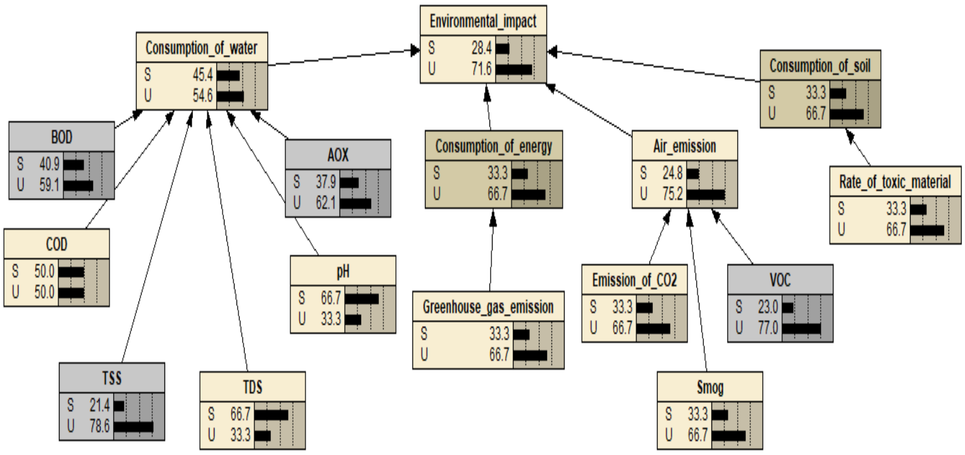

Fig. 8. Scenario analysis 1 of simultaneous change of BOD, TSS, AOX and VOC.

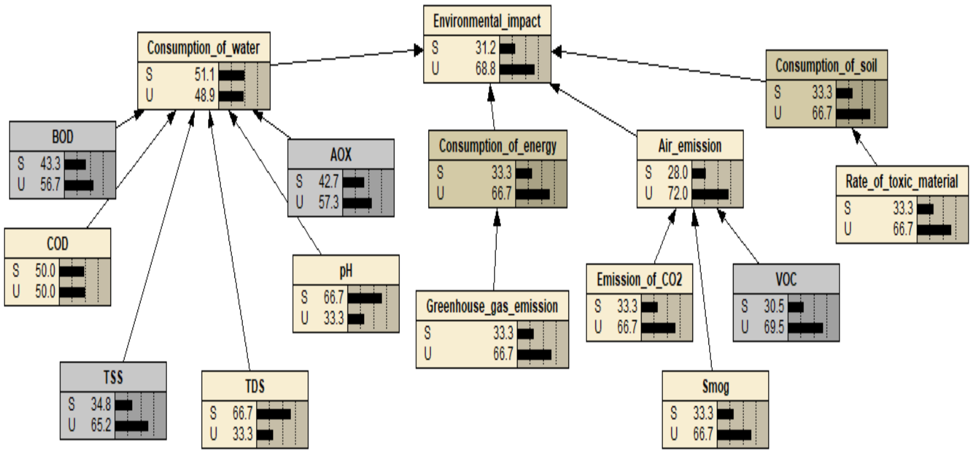

Fig. 9. Scenario analysis 2 of simultaneous change of BOD, TSS, AOX and VOC.

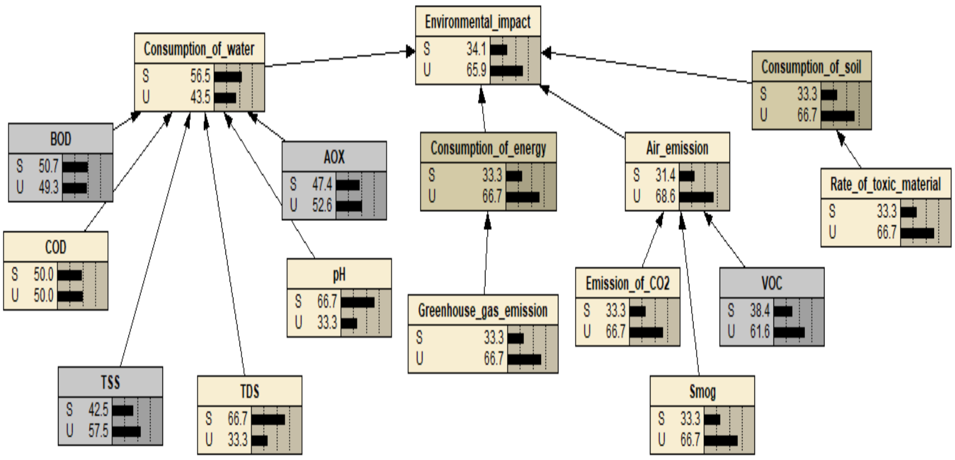

Fig. 10. Scenario analysis 3 of simultaneous change of BOD, TSS, AOX and VOC.

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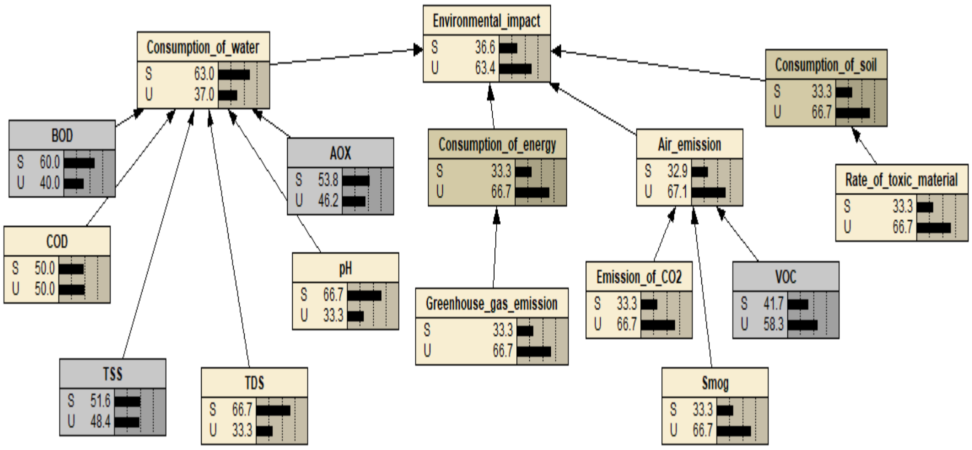

Fig. 11. Scenario analysis 4 of simultaneous change of BOD, TSS, AOX and VOC.

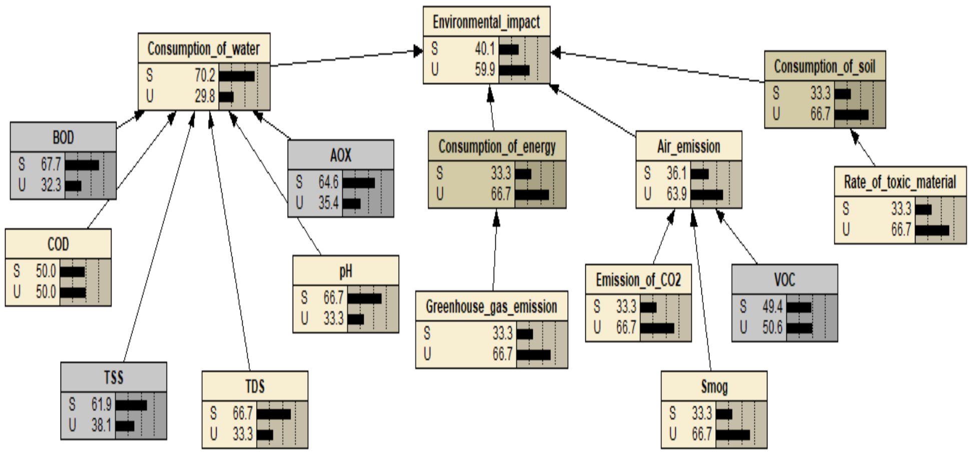

Fig. 12. Scenario analysis 5 of simultaneous change of BOD, TSS, AOX and VOC.

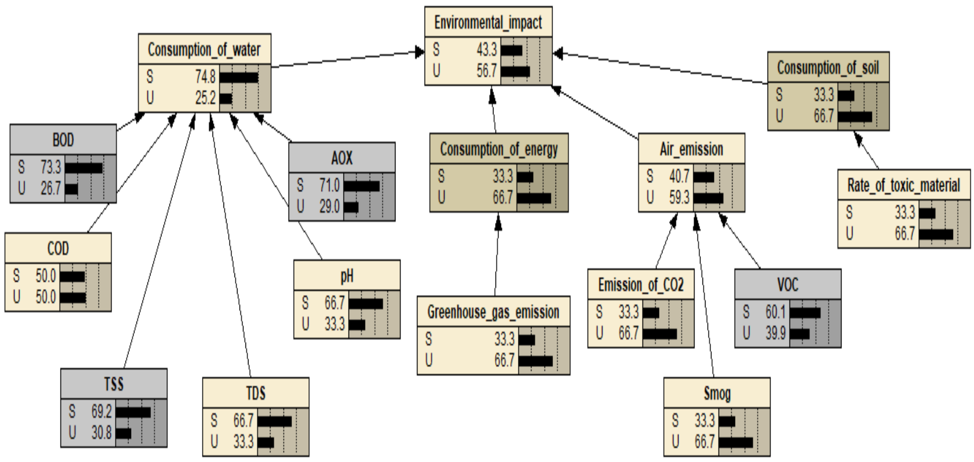

Fig. 13. Scenario analysis 6 of simultaneous change of BOD, TSS, AOX and VOC.

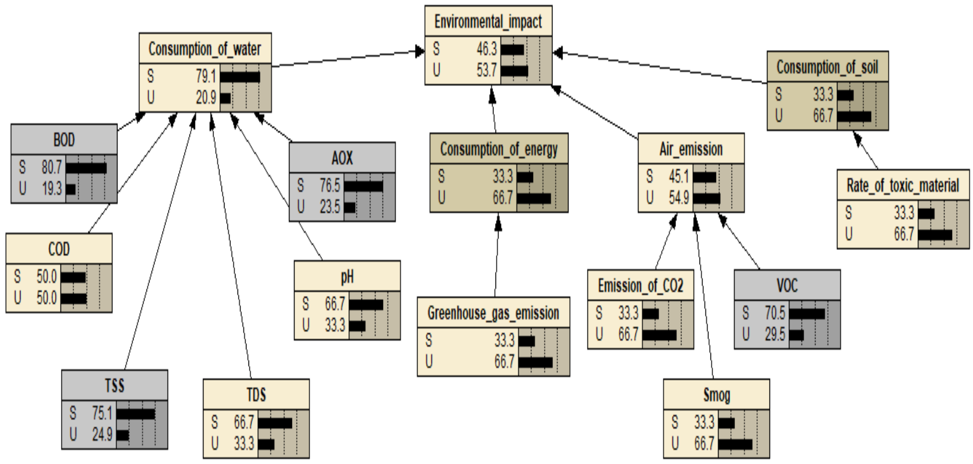

Fig. 14. Scenario analysis 7 of simultaneous change of BOD, TSS, AOX and VOC.

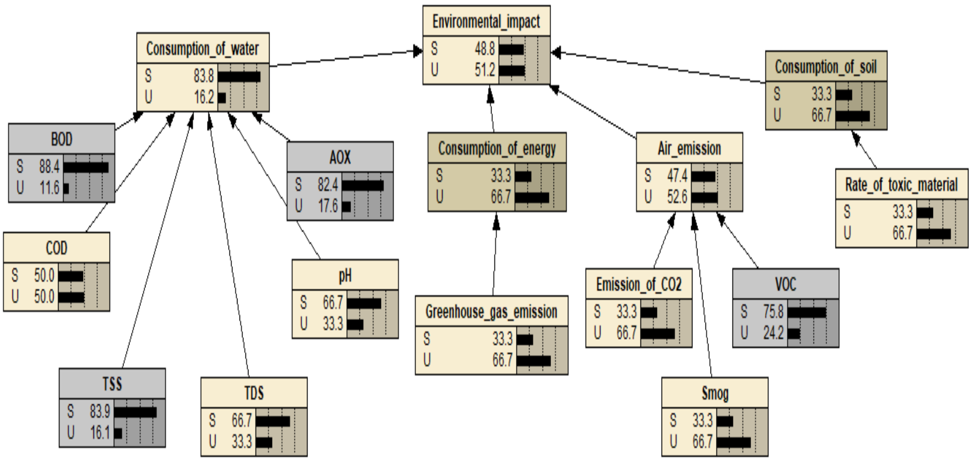

Fig. 15. Scenario analysis 8 of simultaneous change of BOD, TSS, AOX and VOC.

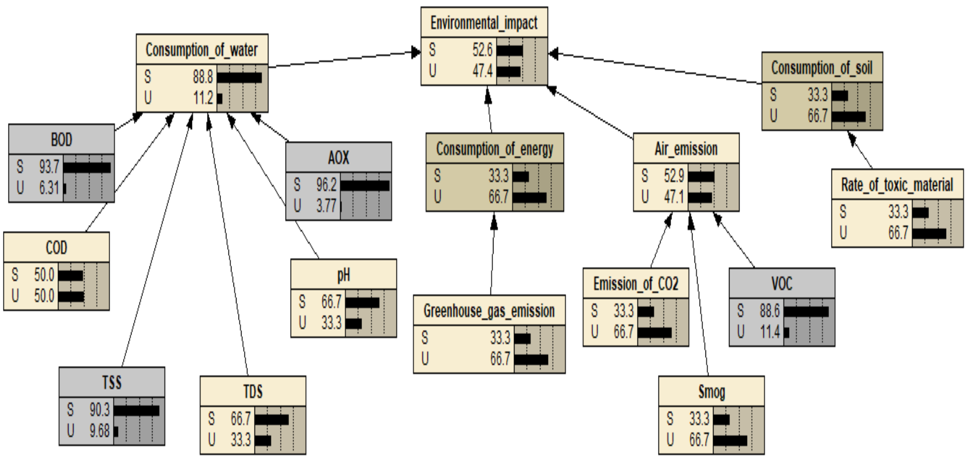

Fig. 16. Scenario analysis 9 of simultaneous change of BOD, TSS, AOX and VOC.

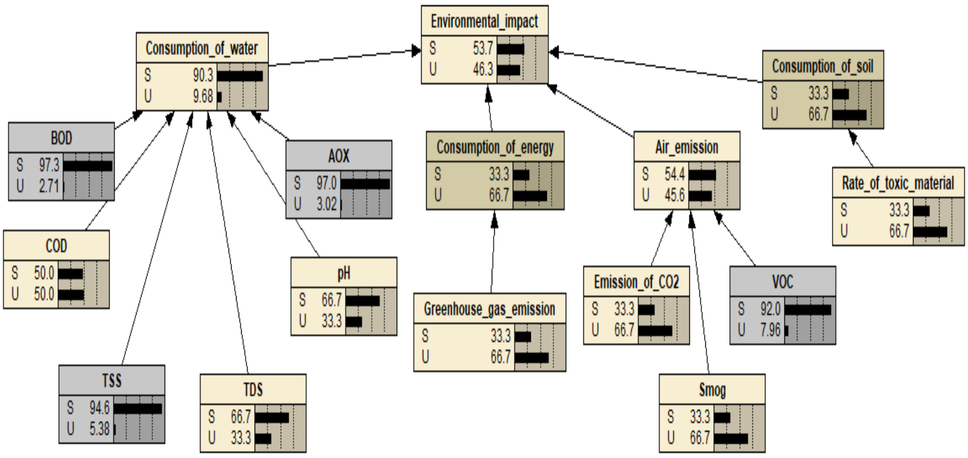

Fig. 17. Scenario analysis 10 of simultaneous change of BOD, TSS, AOX and VOC.

Outcome: these ten possibilities all represent the model's expected behavior. When the selected indicators were improved then environmental impact was also improved simultaneously that are illustrated in table. Similarly, different combinations of performance indicators are explored to construct alternative scenarios, and the probability distribution of their environmental impact is assessed to provide model verification. In *Table 5* satisfactory is indicated as S, unsatisfactory is indicated as U, and results using Netica software is given below:

Table 5. The presented BBN-based model's scenario analysis findings.

Nodes	States	Conditional Probabilities of Different Scenarios (%)									
		Sc1	Sc2	Sc3	Sc4	Sc5	Sc6	Sc7	Sc8	Sc9	Sc10
BOD	S	40.9	43.3	50.7	60.0	67.7	73.3	80.7	88.4	93.7	97.3
	U	59.1	56.7	49.3	40.0	32.3	26.7	19.3	11.6	6.31	2.71
TSS	S	21.4	34.8	42.5	51.6	61.9	69.2	75.1	83.9	90.3	94.6
	U	78.6	65.2	57.5	48.4	38.1	30.8	24.9	16.1	9.68	5.38
AOX	S	37.9	42.7	47.4	53.8	64.8	71.0	76.5	82.4	96.2	97.0
	U	62.1	57.3	52.6	46.2	35.4	29.0	23.5	17.6	3.77	3.02
VOC	S	23.0	30.5	38.4	41.7	49.4	60.1	70.5	75.8	88.6	92.0
	U	77.0	69.5	61.6	58.3	50.6	39.9	29.5	24.2	11.4	7.96
Consumption of water	S	45.4	51.1	56.5	63.0	70.2	74.8	79.1	83.8	88.8	90.3
	U	54.6	48.9	43.5	37.0	29.8	25.2	20.9	16.2	11.2	9.68
Air emission	S	24.8	28.0	34.1	32.9	36.1	40.7	45.1	47.4	52.9	54.4
	U	75.2	72.0	68.6	67.1	63.9	59.3	54.9	52.6	47.1	45.6
Environmental impact	S	28.4	31.2	34.1	36.6	40.1	43.3	46.3	48.8	52.6	53.7
	U	71.6	68.8	65.9	63.4	59.9	56.7	53.7	51.2	47.4	46.3

4.2.2 | Quantitative analysis

Quantitative analytics in business employs such characteristics to produce information that managers can use to make effective decisions. Looking at real facts, or numbers, is a part of quantitative analysis. This analysis was done by sensitivity analysis.

A sensitivity analysis was used to determine the influence of each unique element in the model output. This analysis shows how small changes in input factors such as emission of CO_2 and TSS can alter the prediction model, which in this case is environmental impact. Entropy measures the impurity of collection of datasets. Information gain is a measure of the decrease in disorder achieved by partitioning the original data set. The reduction in entropy or surprise achieved by changing a dataset is known as information gain, and it is frequently utilized in the training of decision trees. The entropy of a database during a modification is used to calculate information gain. The steps for sensitivity analysis are shown in *Fig. 18*.

Fig. 18. Framework for sensitivity analysis.

The formulae for this analysis are given below:

Entropy, E(d):

$$E\ d) = -\sum_{i-1}^{n} p_i \log_2 p_i).$$

Where,

pi = probability of state,

K = no of state for every indicators / measures.

d = the indicator / measure.

Entropy for a partition, E(d,a):

$$E\ d, a) = \sum \frac{n_j}{n} * E(d_j).$$

Where,

n_j/n = probability of the selected state of environmental impact.

E(d_j) = Entropy of the selected state of indicators / measures.

Information gain, I(d,a):

Where,

E(d) = Entropy of environmental impact.

E(d,a) = Entropy for an indicator / a measure.

$$I\ d, a) = E\ d) - E\ d, a).$$

Calculation of information gain for indicators: entropy calculation for BOD is done as follows:

From the previous table we get data for BOD:

I. Satisfactory state of BOD = 33.3%,
II. Unsatisfactory state of BOD = 66.7%,
III. So, probability of satisfactory state = 0.333,
IV. Probability of unsatisfactory state = 0.667,
V. Entropy for satisfactory state = - (0.333*log2 (0.333)) = 0.528273,
VI. Entropy for unsatisfactory state = - (0.667*log2 (0.667)) = 0.389689,
VII. Total entropy for BOD = 0.917962.

Similarly, we calculated all other indicators and performance measures of entropy by MS Excel and the results are summarized in *Table 6* and *7*.

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Table 6. Entropy for indicators.

Name of Indicators	Entropy of Satisfactory State	Entropy of Unsatisfactory State
BOD	0.528273	0.389689
COD	0.5	0.5
TSS	0.389689	0.528273
TDS	0.389689	0.528273
PH	0.389689	0.528273
AOX	0.528273	0.389689
Greenhouse gas emission	0.528273	0.389689
Emission of Co_2	0.528273	0.389689
Smong	0.528273	0.389689
Voc	0.431207	0.219588
Rate of toxic material	0.528273	0.389689

Table 7. Entropy for performance measures.

Performance Measures	Entropy of Satisfactory State	Entropy of Unsatisfactory State	Total Entropy
Consumption of water	0.527938	0.44706	0.974898
Consumption of energy	0.528273	0.389689	0.917962
Air emission	0.481312	0.280677	0.761989
Consumption of soil	0.528273	0.389689	0.197962
Environmental impact	0.505786	0.322465	0.828252

Calculation of combined entropy and information gain for indicators and performance measures: from figure, it can be seen that, the satisfactory state of environmental impact is 26.1% and unsatisfactory state is 73.9%. So, their probability (n_j/n) will be respectively 0.261 and 0.739.

Partition for BOD, E(d,a)= (0.528273*0.261) + (0.389689*0.739) = 0.425859446.

Similarly, we calculated combined entropy for other indicators and measures by MS Excel using formula and summarized the findings in *Table 8*. Then for next step calculated information gain/entropy reduction for all indicators and measures. The calculation for BOD is shown below:

Information gain for BOD, I(d,a)=E(d)-E(d,a)= 0.828252 – 0.425859446 = 0.402392194.

For other indicators and measures information gain were calculated by MS Excel that are given below in *Table 8* and *Table 9*.

Table 8. Combined entropy and information gain of indicators.

Name of Indicators	Combined Entropy, E(d, a)	Information Gain, I(d, a)= E(d)-E(d, a)
BOD	0.425859446	0.402392194
COD	0.5	0.32825164
TSS	0.274820994	0.553430646
TDS	0.492102694	0.336148946
PH	0.492102694	0.336148946
AOX	0.425859446	0.402392194
Greenhouse Gas Emission	0.425859446	0.402392194
Emission of Co_2	0.425859446	0.402392194
Smong	0.425859446	0.402392194
VOC	0.274820994	0.553430646
Rate of toxic material	0.425859446	0.402392194

Table 9. Combined entropy and information gain of performance measures.

Name of Performance Measures	Combined Entropy, E(d, a)	Information Gain, I(d, a)= E(d)-E(d, a)
Consumption of water	0.4681433	0.3610834
Consumption of energy	0.425859446	0.402392194
Air emission	0.333043004	0.495208636
Consumption of soil	0.425859446	0.402392194

The outcome of sensitivity analysis of indictors and performance measures represent in *Fig. 18* and *Fig. 19*.

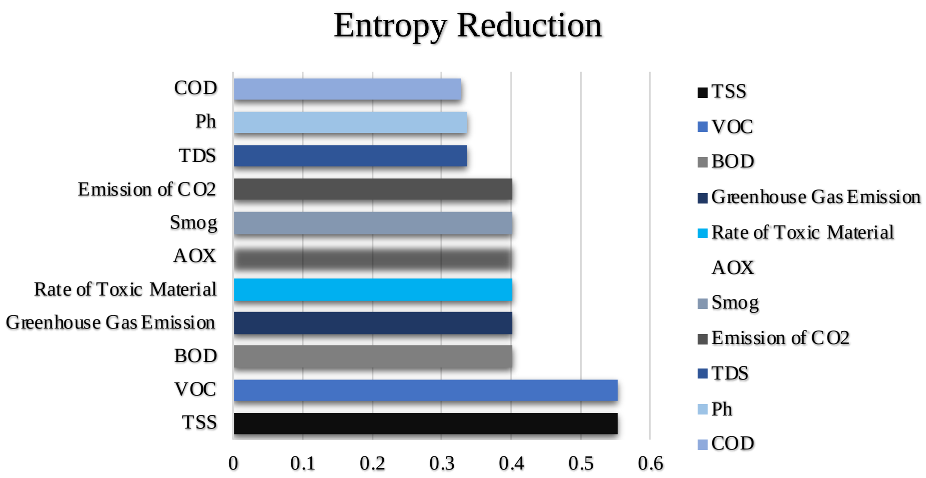

Fig. 18. Sensitivity analysis of environmental impact for indicators.

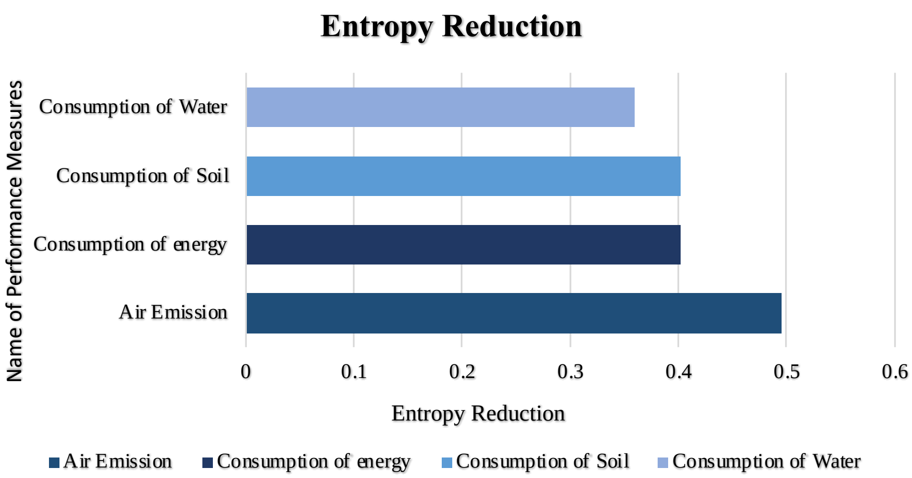

Fig. 19. Sensitivity analysis of environmental impact for performance measures.

Outcome: sensitivity analysis enables the decision-maker to find the input parameters that have the greatest impact on the output and emphasize them in the choice process. From *Fig. 18* and *Fig. 20*, managers should decide what he/she should focus for lowering environmental impact. If the manager chooses indicators, then he/she should prioritize to decrease TSS and VOC and if the manager choose performance measures then he/she should focus to decrease air emission.

Diagnostic analysis takes the insights gained from descriptive analytics and delves down to find the reasons of those outcomes. Organizations make advantage of this type of analytics as it generates more linkages between data and finds patterns of activity. A diagnostic analysis can be used to calculate the marginal probability of base or parent nodes. This methodology can be used to find the prior probability dependent on the pooled risk. *Table 10* and *Fig. 20* and *21* show the confidence level of the current node conditioned on aggregated risk.

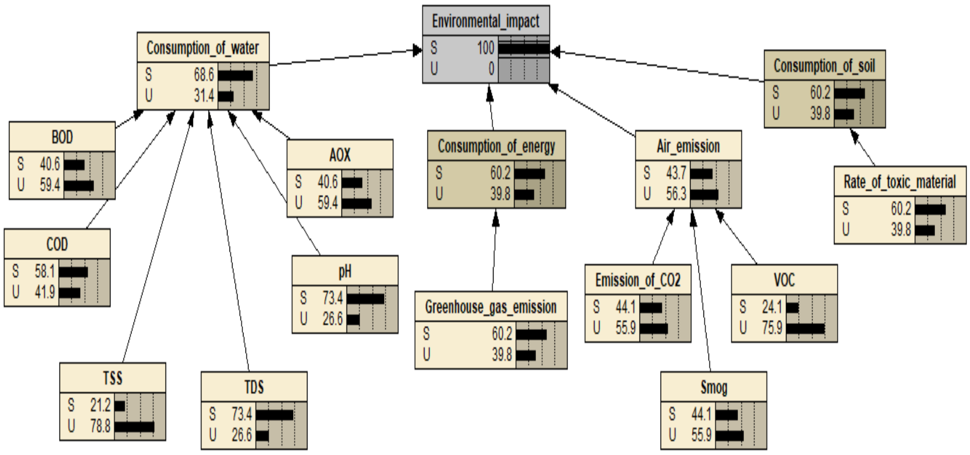

Fig. 20. Parent node posterior probabilities based on environmental impact satisfactory state.

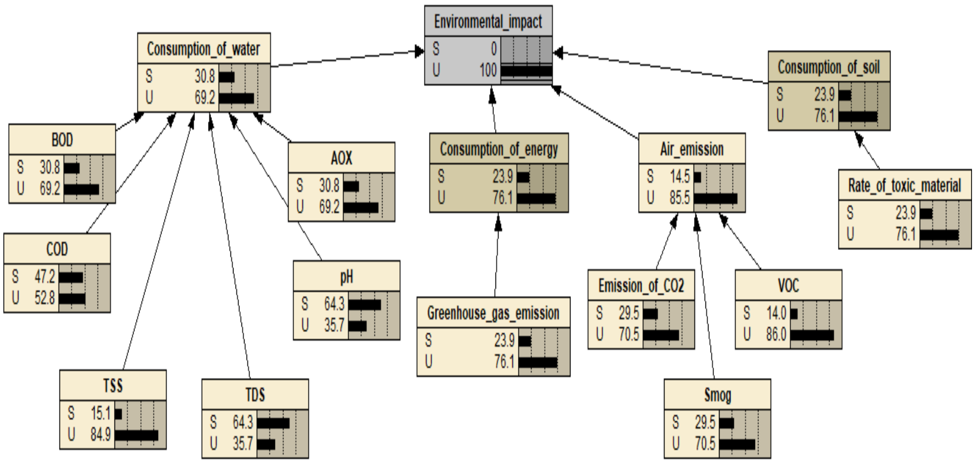

Fig. 21. Parent node posterior probabilities based on environmental impact unsatisfactory state.

Table 10. Parent node posterior probabilities based on environmental performance.

Parent Nodes	Posterior Probabilities of States	Environmental Impact Satisfactory	Environmental Impact Unsatisfactory
BOD	Satisfactory	0.406	0.308
	Unsatisfactory	0.594	0.692
COD	Satisfactory	0.581	0.472
	Unsatisfactory	0.419	0.528
TSS	Satisfactory	0.212	0.151
	Unsatisfactory	0.788	0.849
TDS	Satisfactory	0.734	0.643
	Unsatisfactory	0.266	0.357
PH	Satisfactory	0.734	0.643
	Unsatisfactory	0.266	0.357
AOX	Satisfactory	0.406	0.308
	Unsatisfactory	0.594	0.692
Greenhouse gas emission	Satisfactory	0.602	0.239
	Unsatisfactory	0.398	0.761
Emission of Co2	Satisfactory	0.441	0.295
	Unsatisfactory	0.559	0.705
Smong	Satisfactory	0.411	0.295
	Unsatisfactory	0.559	0.705
VOC	Satisfactory	0.241	0.14
	Unsatisfactory	0.759	0.86
Rate of toxic material	Satisfactory	0.602	0.239
	Unsatisfactory	0.314	0.692

Outcome: in two extreme situations of environmental performance, *Table 10* demonstrates the change

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in the probability of performance indicators and measures. When environmental performance swings from an unsatisfactory to a satisfactory state, all the chances for an unsatisfactory state drop. On the other side, the chances of being in a satisfied state increase. This is consistent with the model's expected behavior.

5 | Discussions

Following a review of the available literature, eleven green supply chain performance indicators and four green supply chain performance measures were chosen, and BBN was used to develop the model that would predict total environmental performance. Collected data about the indicators from a renowned industry were used for analysis in Netica software. Here, we considered two states for BBN model; one was satisfactory state and another one was unsatisfactory state. This model will give the decision-makers an overview of the total environmental performance of the green supply chain. For evaluating the model, qualitative and quantitative analysis were done. In qualitative analysis, extreme condition test and scenario analysis were done. This will enable the management to see how the performance metrics affect the overall performance of the green supply chain. Again, in quantitative analysis, sensitivity analysis was done. A sensitivity analysis identifies the most critical performance indicators and offers a ranking of the metrics in order of priority to decision-makers. The outcome TSS and VOC were found to be the most important indicators for the case company in this study, with the highest entropy reduction. And 'air emission' was the most impactful performance measures among the four. By this, manager could give focus on reducing high TSS, high VOC and air emission. This methodology can also assist a manager in meeting the predetermined GSCM performance goals.

6 | Conclusions

This research used BBN model for anticipating performance indicators and measures for environmental impact. For validation of the BBN model some analyses were done. These all analysis provided a message that if indicators satisfactory state is increased then the overall environmental impact will be good but if not, then then overall environmental impact will be bad. Among them sensitivity analysis proved that for reducing environmental impact a decision maker should focus either on indicator 'TSS' and 'VOC' or performance measure of 'air emission'. In this way, unsatisfactory state of environmental impact would be reduced. For reducing TSS, VOC, and air emission a manager needs to choose a proper green raw material so that environment will not be hampered as well as it will be effective to earn more profit, and this is the focus of GSCM.

SC managers will be able to identify the significant performance indicators that most affect GSCM performance of their company using this model. They will also be able to prioritize and allocate resources for the performance indicators for highest environmental performance. Moreover, the managers will be able to monitor current environmental performance and set the target performance indicator level target accordingly.

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Conflicts of Interest

All co-authors have seen and agree with the contents of the manuscript and there is no financial interest to report. We certify that the submission is original work and is not under review at any other publication.

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