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Green Supply Chain Performance Prediction Using a Bayesian Belief Network

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Abstract: Green supply chain management (GSCM) has emerged as an important issue to lessen the impact of supply chain activities on the natural environment, as well as reduce waste and achieve sustainable growth of a company. To understand the effectiveness of GSCM, performance measurement of GSCM is a must. Monitoring and predicting green supply chain performance can result in improved decision-making capability for managers and decision-makers to achieve sustainable competitive advantage. This paper identifies and analyzes various green supply chain performance measures and indicators. A probabilistic model is proposed based on a Bayesian belief network (BBN) for predicting green supply chain performance. Eleven green supply chain performance indicators and two green supply chain performance measures are identified through an extensive literature review. Using a real-world case study of a manufacturing industry, the methodology of this model is illustrated. Sensitivity analysis is also performed to examine the relative sensitivity of green supply chain performance to each of the performance indicators. The outcome of this research is expected to help managers and practitioners of GSCM improve their decision-making capability, which ultimately results in improved overall organizational performance.

Keywords: green supply chain; performance measurement; Bayesian belief network; sustainability

1. Introduction

Recently, supply chain performance prediction has received increased attention from academics and practitioners [1]. To predict the supply chain performance, the development of supply chain performance metrics is crucial. Developing a performance measurement system to empower the coordination mechanism for mutual decision-making has become a vital issue in supply chain management [2]. This mutual decision-making process can be used to combine the goals of independent participants and integrate their individual activities so as to optimize the performance of the whole supply chain [3]. Hoole [4] discussed that the performance measurement of a supply chain enables a company to employ more mature supply chain practices and, consequently, enables them to reduce cost faster than their less mature competitors. More accurately, there can be a variation of 5% to 6% of annual revenue in supply chain costs among competitor companies of the same industry. Therefore, it is important for a company to develop a performance measurement model to improve its operation [5,6].

Companies are presently trying to include environmental performance in the evaluation of the overall supply chain performance because of increased competitive, regulatory, and community

pressures [3]. Companies need to minimize the environmental impact of their goods and services and, thus, they have to formulate as well as implement strategies. Consequently, it helps companies to compensate competitive, community and regulatory pressures and also helps them to achieve environmental sustainability [7–9]. The basic principles upon which a company's business is based can be reviewed and readjusted so that the company can project a green image. In addition, Bhattacharya et al. [10] discussed that it is important for a company to address environmental issues to develop a unique competitive advantage for increasing the value of its core business programs. In 1994, the Confederation of British Industries observed various elements that build a competitive advantage through environmental performance: market expectations, risk management, regulatory compliance and business efficiency are some of these elements [11–13]. To handle all these elements properly, researchers and practitioners use green supply chain management (GSCM) as an effective tool [14,15]. Thus, GSCM enables a company not only to increase its ecological efficiency but also to increase profit and market share. It also results in sustainable growth [7].

Green supply chain performance prediction is receiving more and more attention because of the recent progress in the area of GSCM. Though several metrics have been suggested for supply chain performance measurement [16–19], these metrics do not include all aspects of the green supply chain. So, more comprehensive environmental performance metrics need to be introduced. This study aims to identify these performance indicators and use them to predict green supply chain performance in different scenarios.

There are significant works completed on traditional supply chain performance measurement but very few of them focused on the environmental performance of the supply chain. Gunasekaran et al. [20] described various supply chain performance metrics. Though they did not include environmental performance metrics, they emphasized a more comprehensive study of these general measures. In addition, works completed on environmental performance measurement mostly considered qualitative performance measures and indicators. Hervani et al. [21] considered ISO14031 to develop the basic principle for green supply chain performance measurement, but no definite quantitative model was suggested in their study. So, all of the existing literature lacks developing and implementing probabilistic and quantitative techniques to predict green supply chain performance. Therefore, the research questions this study aims to answer are:

(a) What are the performance metrics of a green supply chain?
(b) How do the performance metrics affect the supply chain performance?
(c) Which metrics have the most impact on GSCM performance?
(d) How can a manager achieve a specified level of GSCM performance?

This study attempts to answer the above research questions by identifying the GSCM performance measures by reviewing the existing literature and taking expert opinion, developing a quantitative and probabilistic model using a Bayesian belief network (BBN). The effectiveness of the model is demonstrated using a real-world case study, as well as performing sensitivity and diagnostic analyses to determine the impact of various metrics on overall performance. The BBN-based green supply chain performance prediction model can consider the cause–effect relationships between different performance indicators and provide informed decisions effectively in cases of incomplete, imprecise and ambiguous information. The proposed BBN model is flexible enough to perform both diagnostic analysis or bottom-up inference, and predictive analysis or top-down inference.

The rest of the paper is organized as follows. Section 2 presents a review of the existing literature on traditional supply chain management performance measurement and GSCM performance measurement. Section 3 gives a brief overview of BBN. Section 4 presents the proposed research framework. Section 5 includes a BBN-based performance prediction model. Data collection and analysis, results, discussion of the findings and sensitivity analysis are also included in this section. Finally, Section 6 includes conclusions, managerial implications and recommendations.

2. Literature Review

In this section, a brief overview of GSCM and review of the related literature is provided. The literature review is divided into two parts. In the first section, the traditional supply chain performance measurement is discussed. In the second section, literature focusing on GSCM is discussed.

2.1. Green Supply Chain Management (GSCM)

GSCM is defined by incorporating the environmental aspect into the supply chain management that considers the effect and association of supply chain management to the surrounding environment [14,19,22,23]. The traditional supply chain focuses on the economic aspect of the supply chain, ignoring the environmental impact of the activities, whereas the green supply chain focuses on and tries to minimize the adverse impact of the supply chain activities on the environment. A green supply chain, however, must not just be environment friendly, it also must be economically viable [14]. According to Wilkreson [24], GSCM is not a cost center. Instead, it is an important business driver.

The rising scarcity of raw materials, environmental pollution and ever-increasing world population have placed utmost importance on GSCM [14,25]. It encompasses two major areas, green design and green operations [25]. Mishra et al. [19] expanded the repertoire of GSCM by adding green distribution and marketing to the definition. Green design is the incorporation of the environmental effect of a product throughout its life cycle in the design and development process [26]. Several tools exist that can help designers understand the impact of their product. Life-cycle assessment, design for environment principles and product stewardship are some of the tools [27]. Green operations include green manufacturing or remanufacturing, reverse logistics and waste management [28–30]. Reverse logistics is a crucial part of GSCM. Reverse logistics is a method of increasing environmental performance of a company by using the concept of the 3Re's (recycle, reuse and reduce the use of material) [10,19,29]. Swami and Shah [31] included the coordination of functional areas to share the responsibility for environmental performance as an important element of GSCM.

2.2. Traditional Supply Chain Management Performance Measurement

Though much work on performance measurement and management of internal organizational activities has been done, only a handful have focused on supply chain performance measurement [18]. Multiple echelon inventory-based supply chain models have generally considered various performance measures like cost, quality, delivery time, inventory levels, and environmental costs [32,33].

Comprehensive supply chain performance measurement has been the focus of some of the existing literature. Supplier performance evaluation and study of appropriate performance measures have received special attention from some researchers [34,35]. Most of these studies have focused on measuring supplier performance, and also focused on their roles in the supply chain. Beamon [36] observed the impact of the various elements on supply chain performance and recognized the inherent association between these elements and supply chain performance. Inventory system stock-out risk, the probability distribution of demand and transportation time are some of the major elements identified by the authors.

A. Gunasekaran et al. [20] described various supply chain performance metrics. Using these performance metrics, they also described sources. Though they did not include environmental performance metrics, they emphasized a comprehensive study of these general measures. As existing literature on traditional supply chain measurement fails to include environmental performance, several researchers have tried to incorporate environmental performance in their different studies. These studies will be reviewed in the next section.

2.3. GSCM Performance Measurement

The perception of ecological sustainability has been considered as a basis for studying management practices by several researchers [37–39]. They have acknowledged its applicability in both operational and strategic contexts. Greening of supply chains within various contexts has been studied and these contexts include product design [26], process design [25], manufacturing practices [40–42], purchasing [43,44], and a comprehensive combination of these factors [25,45].

Several researchers [10,25,46,47] emphasized that GSCM has emerged as an approach to build a competitive advantage and to fulfill the environmental requirements that are set by various regulatory bodies. Ahi and Searcy [48] proposed various metrics to measure environmental performance. Reducing the negative environmental impact (different types of pollution) and reducing the waste of resources (energy, materials, goods) were considered as overall objectives of a green supply chain by Hervani et al. [21]. The authors also noted that this reduction process should start from the extraction of raw material and should continue up to the consumption and shipment of products. Green supplier selection has attracted quite a bit of attention from researchers [49–51]. Several metrics for assessing supplier performance were identified by Kuo, Wang, and Tien [52]. These metrics include "green competencies", "current environment efficiency", "supplier's green image" and "net life-cycle cost". Actually, this supplier performance assessment procedure is a part of the green purchasing process. Yazdani, Chatterjee, Zavadskas, and Zolfani [53] used a Quality Function Development (QFD)-based multi-criteria decision-making approach for green supplier selection. Tang, Wei, and Gao [54] used the Muirhead Mean operator and dual Muirhead Mean (DMM) operator to process the interval-valued Pythagorean fuzzy numbers (IVPFNs), which they then used to solve a supplier selection problem. Jenssen and de Boer [55] incorporated life-cycle assessment in the green supplier selection problem. Xu, Shi, Cui, and Quan [56] used interval 2-tuple linguistic hybrid aggregation operators to select green suppliers.

Researchers have introduced tools such as the analytical hierarchy process (AHP), activity-based costing and design for environmental analysis; life-cycle analysis and balanced scorecard for Green Supply Chain Performance Measurement. Although a few tools can be directly implemented for evaluating the performance, the remaining others need to be modified. For example, a management tool known as ecological supply chain analysis (ECOSCAN) was developed by Faruk et al. [45] to observe the effect of environmental management across the supply chain. The life cycle analysis model is the basis of the ECOSCAN tool, which emphasizes the connection between life-cycle analysis and GSCM methods.

Handfield, Walton, Sroufe, and Melnyk [57] combined AHP with an extensive information system. This information system enables environmentally conscious purchasing. Pineda-Henson, Culaba, and Mendoza [58] used AHP to analyze the impact of environment by following the life-cycle assessment approach, which mainly considers the manufacturing operations. Handfield et al. considered only green purchasing and Pineda-Henson et al. considered a particular case study of pulp and paper manufacturing; however, none of them considered the overall green supply chain performance.

By reviewing the existing literature, eleven corresponding green supply chain performance indicators were identified. These eleven indicators were then classified into a hierarchy model which was inspired by the works of Maleki and Machado [33]. The indicators were first clustered into small groups, e.g., indicators related to water and energy consumption were put into the group 'consumption'. These groups were then classified into performance measures. Two performance measures were considered: business wastage, and emission and consumption. Business wastage, in the context of this paper, is defined as waste materials produced as a result of various business processes. On the other hand, emissions and consumption includes all those indicators related to various solid, liquid emission and different resource consumptions. It is to be noted that two indicators, i.e., 'Output amount of hazardous and toxic material' and 'Percentage of energy obtained from renewable sources' were not clustered into any group as there no performance indicators similar to them. These performance measures and indicators were used for developing a BBN model. Using these performance measures

and indicators, the green supply chain performance in different scenarios can be predicted. These performance measures and indicators are presented in Table 1 along with corresponding references and notations that will be used throughout the paper.

Table 1. Green supply chain performance measures and indicators.

Measures	Groups	Indicators	Reference
Business Wastage related	Materials related.	Total flow quantity of scrap.	[59,60]
		Percentage of materials remanufactured.	[21,61]
		Percentage of materials recycled/re-used.	[15,62]
	Output amount of hazardous and toxic material.		[32,63]
	Waste related.	Amount of solid wastes.	[46,64]
		Amount of liquid wastes.	[46,64]
Emissions and consumption related	Emission.	Amount of greenhouse gas emissions.	[65]
		Air emission quality.	[66,67]
	Consumption.	Amount of water consumption.	[68,69]
		Amount of energy consumption.	[68,69]
	Percentage of energy obtained from renewable source.		[70,71]

3. Bayesian Belief Network

As mentioned before, Bayesian Belief Network is the method of choice for predicting the performance of green supply chain in this study. A Bayesian Belief Network, or Bayes net in short form, is a probabilistic graphical model that presents knowledge about an uncertain domain. Bayes net is an effective method to represent causality and conditional probabilities among various factors [72,73]. Moreover, this method is suitable when the factors are probabilistic in nature. According to several authors, such as Langseth and Portinale; Mahadevan, Zhang, and Smith; Maleki and Machado [33,74,75], BBN shows high performance in handling uncertainty. As the factors and the relationships among them are represented using nodes and edges, any model represented using this method is easier to understand for practitioners than any other techniques [72]. As the performance indicators used in this study are probabilistic and the state of performance measures are conditionally dependent upon the states of performance indicators, Bayesian Network has been chosen to predict environmental performance.

BBN consists of two parts $B = (G, \theta)$. The first part, "G", is a directed acyclic graph (DAG) which includes nodes and arcs. DAG presents the network visually where variables of the data set $X_1, \ldots \ldots, X_n$ represent nodes and arcs indicate dependencies among nodes [76]. The second part of BBN is the conditional dependency distribution of θ where $\theta_{xi|\pi xi} = P_B(x_i|\pi_{xi})$ is the set of direct parent variables of x_i in G [77]. Using the joint probability distribution, the network B can be represented by:

$$P_B(X_1, \ldots, X_n) = \prod_{i=1}^{n} P_B(X_i | \pi_{Xi}) = \prod_{i=1}^{n} X_i | \pi_{Xi} \quad (1)$$

In a BBN, random variables are represented by nodes, and probabilistic dependencies among the corresponding random variables are represented by edges between the nodes. A BBN actually is a probabilistic model that can compute the posterior probability distribution of any unobserved stochastic variables, given the observation of complementary subset variables [78]. In a BBN, "backward" probability propagation is also possible and it is helpful to find the most probable scenario indicating the evidence set [79].

Inference in BBN is used to update the probability for a hypothesis as more evidence or information becomes available. Figure 1 illustrates a simple Bayesian network where "A" and "B" are parent nodes, "C" is a child node. There are two types of inference support: predictive and diagnostic support for a node X_i. Predictive support for node X_i is a top-down approach that considers evidence nodes connected to X_i through its parent nodes. On the other hand, diagnostic support for node X_i is a bottom-up approach that considers evidence nodes connected to X_i through its child node [80].
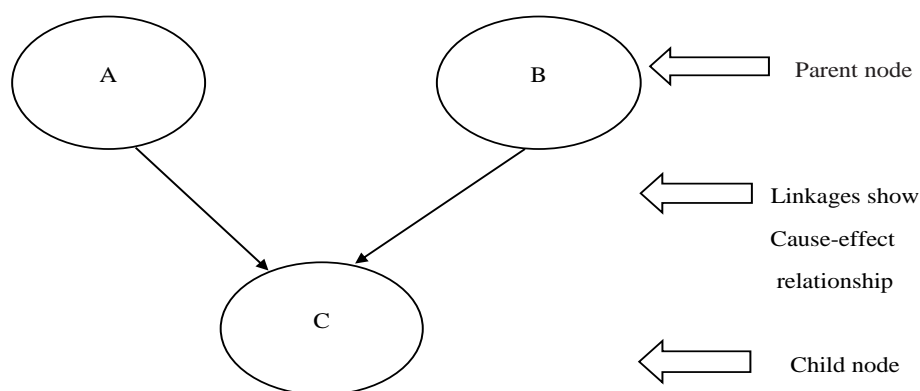
Figure 1. A simple Bayesian network.

4. Framework Development

The aim of this research work is to find out the most significant quantitative green supply chain performance measures and predict green supply chain performance in different scenarios. Figure 2 illustrates the methodology of this research. The proposed research consists of five steps as described below.
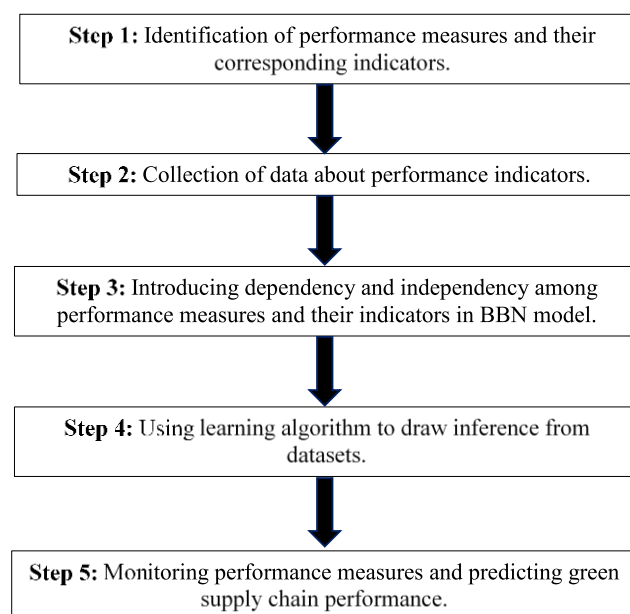
Step 1: Identification of performance measures and their corresponding indicators.

Step 2: Collection of data about performance indicators.

Step 3: Introducing dependency and independency among performance measures and their indicators in BBN model.

Step 4: Using learning algorithm to draw inference from datasets.

Step 5: Monitoring performance measures and predicting green supply chain performance.

Figure 2. Proposed research framework.

Step 1: Identification of performance measures and their corresponding indicators

In the first step, an extensive list of green supply chain performance measures (GSC-PM) is generated based on the factors that have a significant influence on green supply chain performance. The most significant GSC-PM are identified through a literature review. For the literature review, papers published from 1995 to present day were chosen for the review timeline. Literature about green supply chain was searched for factors that the authors believe can significantly affect the environmental performance of a company. Papers about green purchasing, green consumption, green marketing, green manufacturing, green 3R (reduce, reuse, recycle) and supply chain performance measurement were also studied for green performance indicators. A total of 11 performance indicators were identified, which represent two major performance measures. These indicators and measures were identified by reviewing the existing literature.

Step 2: Collection of data about performance indicators

In this step, data about performance indicators were collected. These data were used for calculating the prior probability of each performance indicator in the BBN model and for learning in the BBN model.

Step 3: Introducing dependency and independency among performance measures and their indicators in the BBN model

In this step, dependency and independency among performance measures and their indicators are introduced. They determine the mutual influence between performance measures and their indicators.

Step 4: Using a learning algorithm to draw an inference from data sets

In this step, a learning algorithm is used to draw an inference from data which are collected during step 3. The inference is used to update the probability for a hypothesis (here, the hypothesis is whether the performance indicator will be in a satisfactory state or in an unsatisfactory state) as more evidence or information becomes available.

Step 5: Monitoring performance measures and predicting green supply chain performance by applying evidence to specific nodes in the BBN model

In this step, performance measures are monitored and green supply chain performance is predicted by applying evidence to specific nodes which represent performance indicators in the BBN model. Evidence will be different for different scenarios and, as a result, green supply chain performance will be different for different scenarios. The methodology of this research is illustrated in Figure 2.

5. BBN-Based Performance Prediction Model

5.1. Identification of Performance Measures and Their Corresponding Indicators

Using a thorough literature review, eleven performance indicators have been identified which will be used to build the model.

5.2. Data Collection

The developed methodology has been applied to a real-world case study and used to predict the green supply chain performance of this case company. Necessary data about performance indicators have been collected from this company. These data and information will help to determine the prior probability of the performance indicators being in the satisfactory state, and also the prior probability of performance indicators being in the unsatisfactory state. The data of "Amount of Solid Wastes" performance indicator are highlighted in Table 2 as an example.

Table 2. Data about 'Amount of Solid Wastes' performance indicator.

Time Period (Month)	Amount of Solid Wastes (Kg)	
1st	64,100	
2nd	60,000	
3rd	65,700	
4th	62,000	
5th	59,800	
6th	63,500	
7th	71,000	Recommended Level ≤ 68,000 kg
8th	60,500	
9th	73,000	
10th	70,500	
11th	69,000	
12th	72,000	
13th	68,500	
14th	66,000	
15th	61,000	
16th	66,700	
17th	69,700	
18th	63,300	
19th	67,600	
20th	64,500	

Using a histogram, collected data about performance indicators and their corresponding recommended levels are presented in Figure 3.
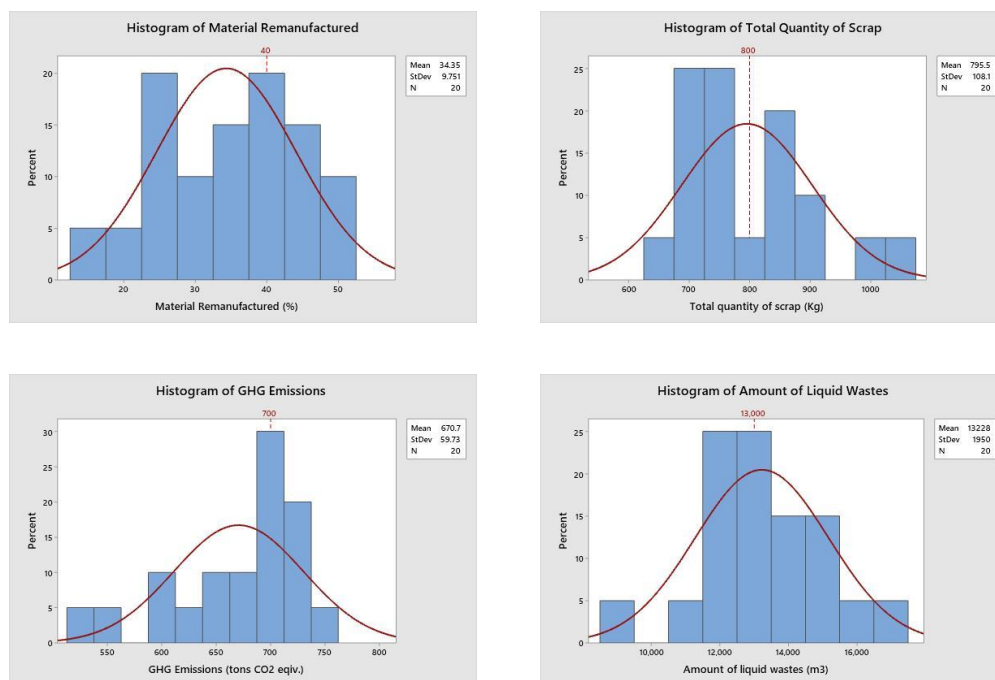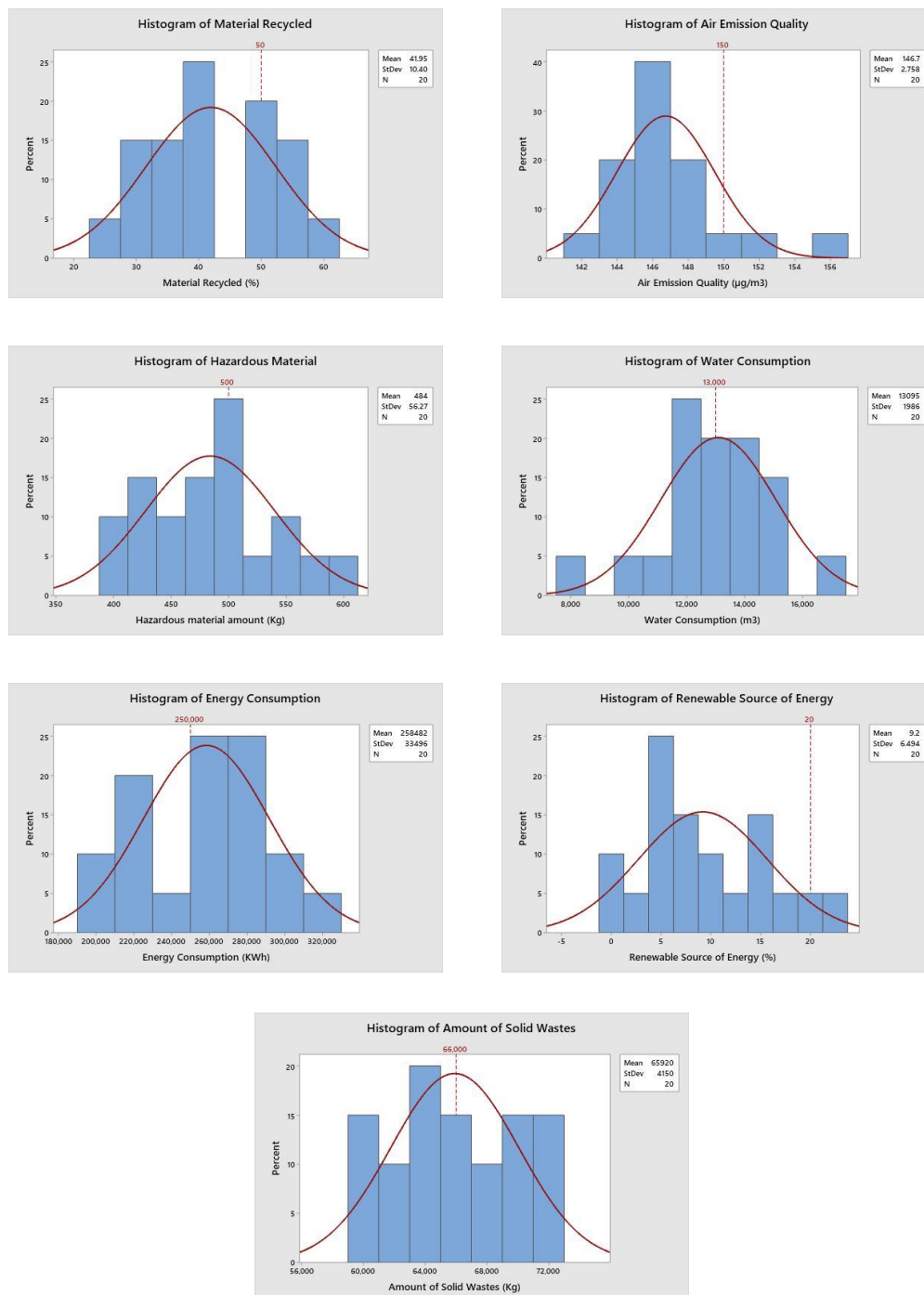

Figure 3. *Cont.*

**Figure 3.** Histogram of performance indicators.

According to Table 2, the company has met the recommended level 13 out of 20 times. For this, the probability that performance indicator "Amount of Solid Wastes" will be in the Satisfactory state = $((13/20) \times 100)\% = 65\%$ and Unsatisfactory state = $((7/20) \times 100)\% = 35\%$. Similarly, prior probabilities for other performance indicators have been calculated and are listed in Table 3.

Table 3. Prior probabilities for green supply chain performance indicators.

Performance Indicators	State Probability (%)	
	Satisfactory (S)	Unsatisfactory (U)
1. Total flow quantity of scrap.	60	40
2. Percentage of materials recycled/re-used.	35	65
3. Percentage of materials remanufactured.	40	60
4. Output amount of hazardous and toxic material.	60	40
5. Amount of solid wastes.	65	35
6. Amount of liquid wastes.	55	45
7. Amount of water consumption.	50	50
8. Amount of greenhouse gas emissions.	60	40
9. Air emission quality.	90	10
10. Amount of energy consumption.	35	65
11. Percentage of energy obtained from renewable sources.	10	90

5.3. BBN Model Development

The BBN model was developed using commercially available software Netica [81] and prior probabilities of performance indicators listed in Table 3 are presented in Figure 4. To learn the conditional probabilities in the network, Netica has counting algorithms, expectation-maximization (EM) and gradient descent [79]. As there are no hidden variables or incomplete data, Netica used counting algorithms for the model development.
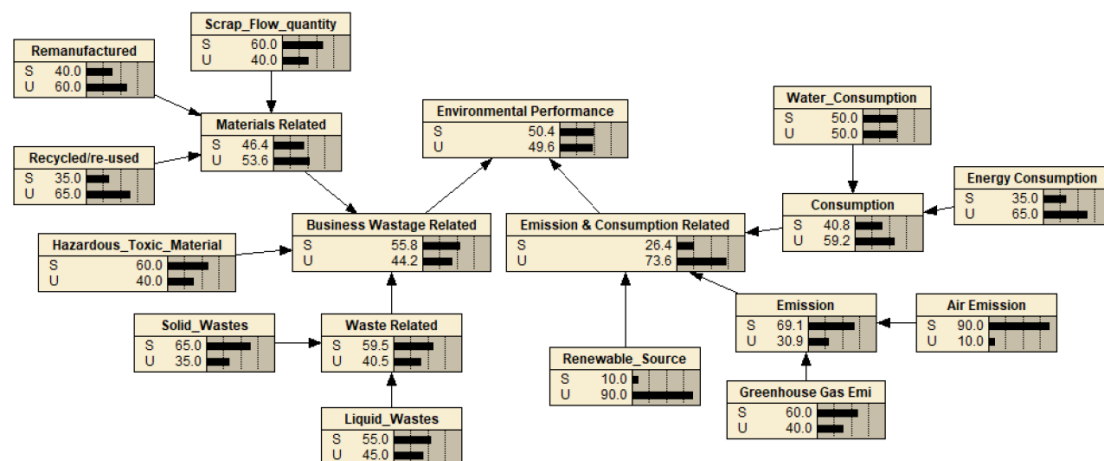
Figure 4. BBN Model for predicting Green Supply Chain performance.

From Figure 4, it can be found that there is a 52.4% probability that performance measure "Business Wastage" will be in a satisfactory state and 53.6% probability that performance measure "Emissions" will be in a satisfactory state and, finally, there is a 57.6% probability that Environmental Performance or Green Supply Chain Performance will be in a satisfactory state. These results are based on current prior probabilities of performance indicators which were collected from the data.

5.4. Model Validation

Both qualitative (extreme-condition test and scenario analysis) and quantitative (sensitivity analysis) validation approaches were performed for validation of the proposed model [82].

5.4.1. Extreme-Condition Test

To validate the model, two extreme conditions are considered in this paper. In extreme case 1, all the performance indicators are in a satisfactory condition. In extreme case 2, all the performance indicators are in an unsatisfactory condition. The results for extreme cases 1 and 2 are shown in Figures 5 and 6, respectively. From Figure 5, it can be found that, when all the performance indexes have a 100 percent probability of being satisfactory, the environmental performance has a 92.8 percent probability of being in a satisfactory condition. Similarly, according to Figure 6, when all the performance indicators have a 100 percent probability of being in an unsatisfactory condition, the environmental performance has only 4.15 percent probability of being in a satisfactory condition. So, the extreme-condition tests show that the proposed environmental performance model works according to expected model behavior.
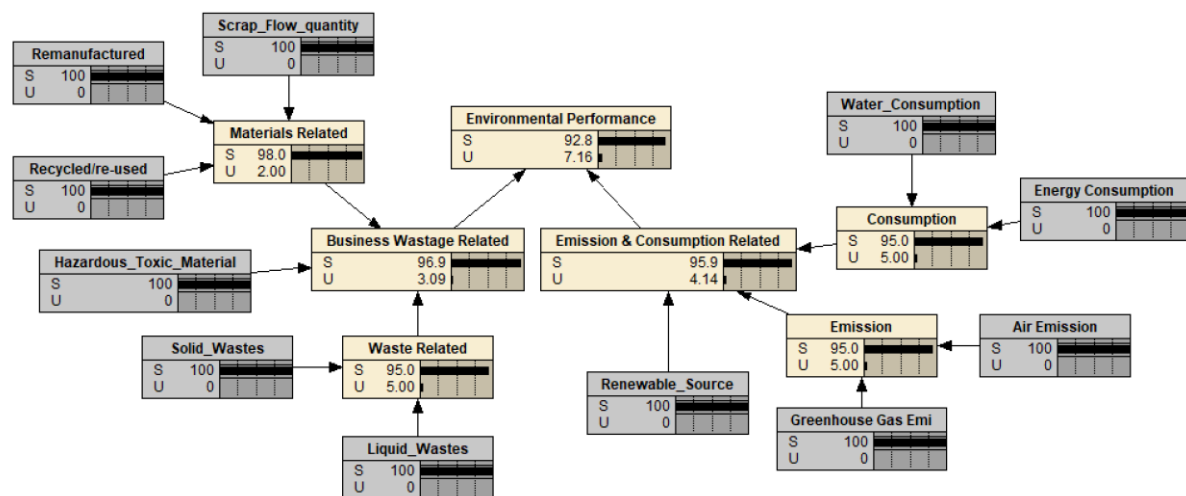

Figure 5. Extreme 1 case when all the performance indicators are in satisfactory states.
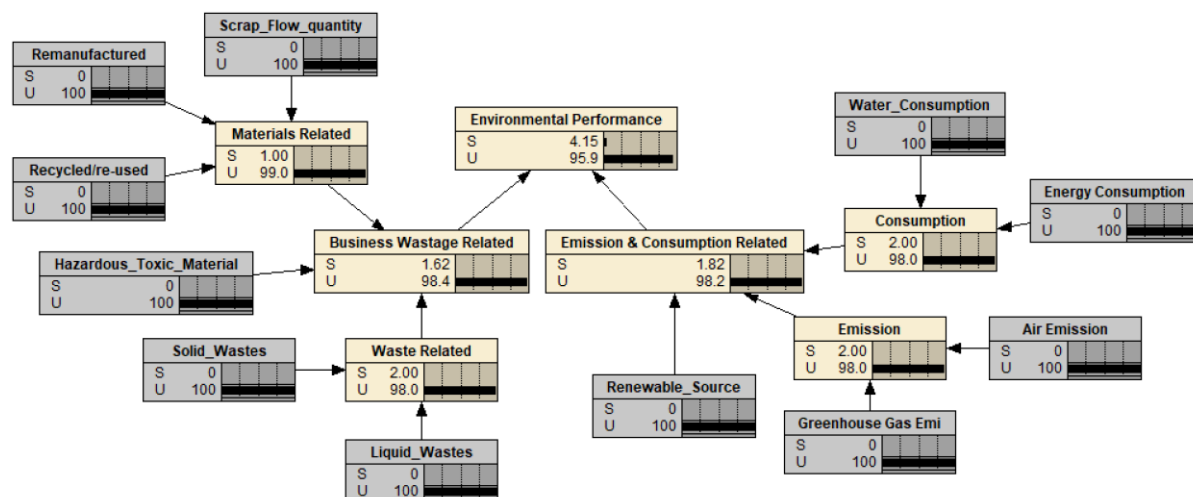

Figure 6. Extreme 2 case when all the performance indicators are in unsatisfactory states.

5.4.2. Scenario Analysis

In this analysis, different hypothetical scenarios are considered except the two extreme cases. Due to space limitations, only two performance factors, namely, *Scrap_Flow_quantity* and *Hazardous_Toxic_Material* have been considered here. Eight different scenarios are considered where the probability of a satisfactory state of these two performance factors is varied from 90 percent to 10 percent in increments of 10 percent. The results of the analysis are shown in Figure 7 and summarized in Table 4.
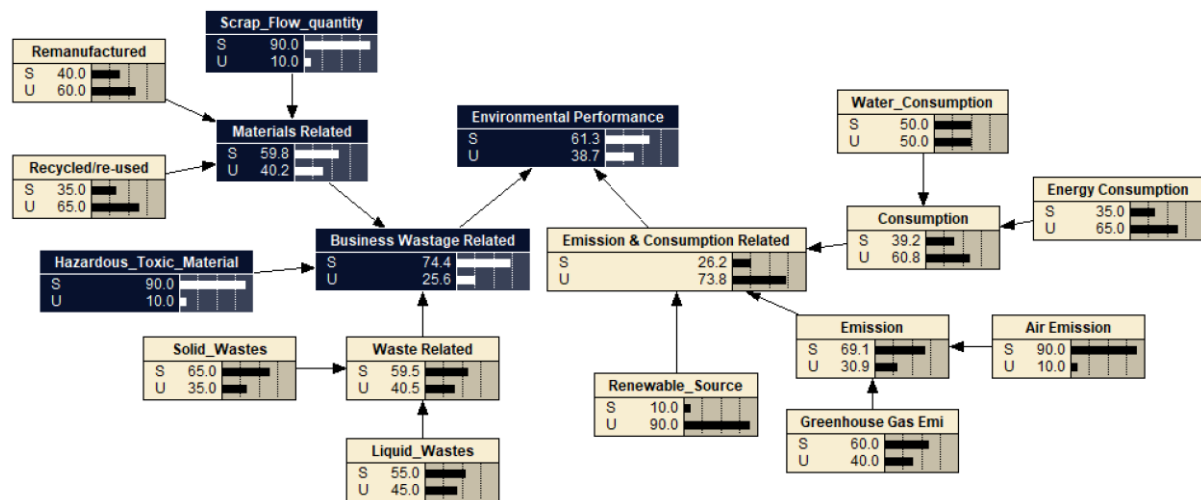
Figure 7. Scenario analysis of simultaneous change of *Scrap_Flow_quantity* and *Hazardous_Toxic_Material*.

Table 4. Scenario analysis results of the proposed BBN-based model.

Nodes	Sates	Conditional Probabilities of Different Scenarios							
		Sc-1	Sc-2	Sc-3	Sc-4	Sc-5	Sc-6	Sc-7	Sc-8
Scrap_Flow_quantity	Satisfactory	90	80	70	50	40	30	20	10
	Unsatisfactory	10	20	30	50	60	70	80	90
Hazardous_Toxic_Material	Satisfactory	90	80	70	50	40	30	20	10
	Unsatisfactory	10	20	30	50	60	70	80	90
Materials Related	Satisfactory	59.8	55.4	50.9	41.9	37.4	32.9	28.5	24
	Unsatisfactory	40.2	44.6	49.1	58.1	62.6	67.1	71.5	76
Business Wastage Related	Satisfactory	74.4	68.2	62	49.6	43.5	37.3	31.1	25
	Unsatisfactory	25.6	31.8	38	50.4	56.5	62.7	68.9	75
Environmental Performance	Satisfactory	61.3	57.6	54	46.6	43	39.3	35.7	32
	Unsatisfactory	38.7	42.4	46	53.4	57	60.7	64.3	68

In scenario 1, where *Scrap_Flow_quantity* and *Hazardous_Toxic_Material* are at 90 percent, Environmental Performance is at 61.3 percent. In scenario 2, where the probability of satisfactory states of performance indicators decreases to 80 percent, the nvironmental performance decreases to 57.6 percent. Scenario 3 depicts 70 percent satisfactory probability of performance indicators where *Environmental Performance* decreases to 54 percent. Similarly, from scenarios 4–8, where the probability of a satisfactory state of *Scrap_Flow_quantity* and *Hazardous_Toxic_Material* decreases, the probability of *Environmental Performance* being in a satisfactory state also decreases. In scenario 8, where the performance indicators are at 10 percent of the probability of being in a satisfactory state, the *Environmental Performance* has only a 32 percent probability of being in a satisfactory state. Thus, the scenarios show the expected model behavior.

All these eight scenarios represent the anticipated model behavior. In a similar way, the different combinations of the performance indicators are considered to generate different scenarios and their *Environmental Performance* probability distribution is tested to perform model validation.

5.4.3. Sensitivity Analysis

To identify the contribution of each individual input in the model output, a sensitivity analysis was performed. This analysis provides information about how slight variations in input parameters like water consumption and solid wastes can affect the model output, which in this case is Environmental Performance. Because the input variables, in this case, are discretized continuous parent nodes, using a

variance reduction method is recommended [82]. However, the results of an entropy reduction method are also provided.

The variance reduction method calculates the variance reduction of the expected real value of a query node *E* (e.g., *Environmental_Performance*) due to a finding in a varying variable node *I* (e.g., *Recycled/re-used*, *Remanufactured*, *Renewable_Source*). The variance of the real value of *E* given evidence *I*, $V(e|i)$ is computed using the following equation [82,83]:

$$(e|i) = \sum_e p(e|i) \, [Y_e - E(e|i)]^2, \tag{2}$$

where *e* is the state of the query node *E*, *i* is the state of varying node *I*, $p(e|i)$ is the conditional probability of *e* given *i*, Y_e is the numeric value corresponding to state *e* and $E(e|i)$ is the expected value of *E* after the new finding *i* for node *I*.

Entropy reduction calculates the expected reduction in mutual information of *E* from a finding for variable *I* (Kabir et al., 2019). The formula is given below:

$$ER = H(E) - H(E|I) = \sum_e \sum_i P(e,i) \, \frac{\log_2[P(e,i)]}{P(e)P(i)}, \tag{3}$$

where $H(E)$ and $H(E|I)$ are the entropy before the new findings and after the new findings. The results of the sensitivity analysis are provided in Figure 8.
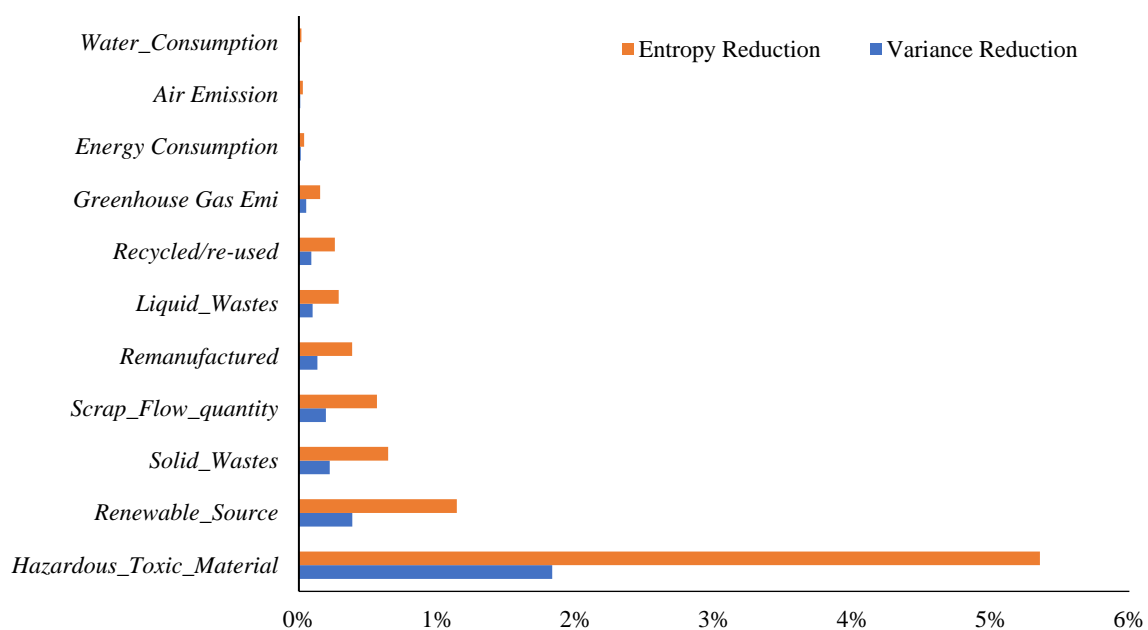

Figure 8. Sensitivity analysis of environmental performance node.

For query node *Environmental_Performance*, *Hazardous_Toxic_Material* has the highest contribution (1.830% variance reduction and 5.354% entropy reduction, respectively) followed by *Renewable_Source* (0.386% and 1.141%), *Solid_Wastes* (0.223% and 0.645%), *Scrap_Flow_quantity* (0.195% and 0.564%), *Remanufactured* (0.133% and 0.385%), *Liquid_Wastes* (0.099% and 0.287%), *Recycled/re-used* (0.090% and 0.260%), *Greenhouse Gas Emission* (0.053% and 0.153%) have medium effects on *Environmetal_Performance*. *Energy_Consumption* and *Air_Emission*, *Water_Consumption* have very low contributions. The variance reduction and entropy reduction for both are below 0.05%. The total contribution of parent nodes in variance reduction is 3.039% and for entropy reduction is 8.856%.

The result of sensitivity analysis allows the decision-maker to identify the input parameters that affect the output most and prioritize them in the decision-making. In the case of *Environmental*

Performance, the managers should first prioritize reducing toxic waste and focus on using renewable sources to improve environmental performance.

5.5. Diagnostic Analysis

Marginal probabilities of root or parent nodes can be determined by performing a diagnostic analysis [83]. The posterior probabilities conditioned to the aggregated risk can be identified using this analysis. The posterior probabilities of the parent nodes conditioned to aggregated risk are shown in Table 5. Table 5 shows the change in the probability of performance indicators in two extreme cases of Environmental Performance. All the probabilities for a satisfactory state decrease when Environmental Performance goes from a satisfactory state to an unsatisfactory state. On the other hand, the probabilities of an unsatisfactory state go up. This is in line with the expected model behavior.

Table 5. Posterior probabilities of parent nodes conditioned to *Environmental Performance*.

Parent Nodes	Posterior Probabilities of States	Environmental Performance	
		Satisfactory	Unsatisfactory
		1	1
Air Emission	Satisfactory	0.906	0.894
	Unsatisfactory	0.094	0.106
Energy Consumption	Satisfactory	0.361	0.339
	Unsatisfactory	0.639	0.661
Greenhouse Gas Emi	Satisfactory	0.622	0.577
	Unsatisfactory	0.378	0.423
Hazardous_Toxic_Material	Satisfactory	0.732	0.466
	Unsatisfactory	0.268	0.534
Liquid_Wastes	Satisfactory	0.581	0.518
	Unsatisfactory	0.419	0.482
Recycled/re-used	Satisfactory	0.378	0.321
	Unsatisfactory	0.622	0.679
Remanufactured	Satisfactory	0.436	0.364
	Unsatisfactory	0.564	0.636
Renewable_Source	Satisfactory	0.137	0.062
	Unsatisfactory	0.863	0.938
Scrap_Flow_Quantity	Satisfactory	0.643	0.556
	Unsatisfactory	0.357	0.444
Solid_Wastes	Satisfactory	0.695	0.605
	Unsatisfactory	0.305	0.395
Water_Consumption	Satisfactory	0.508	0.492
	Unsatisfactory	0.492	0.508

6. Conclusions, Implications and Limitations to This Study

In this study, a BBN-based probabilistic model is proposed for predicting green supply chain performance. Eleven green supply chain performance indicators and two green supply chain performance measures were identified through a review of the existing literature, and then BBN was used to develop the model that would predict the overall environmental performance. Inputting the satisfactory/unsatisfactory states of the performance indicators in the model will provide the decision

maker with the overall green supply chain environmental performance state. This will allow the manager to see how the performance metrics can affect the overall green supply chain performance. To validate the model, an extreme condition test was used. Furthermore, performing a sensitivity analysis reveals the most important performance indicators and provides the decision makers with a ranking of the indicators in the order of importance. For the case company in this study, output amount of hazardous toxic material was found to be the most important indicator having the highest variance reduction and entropy, followed by percentage of energy obtained from renewable sources. Amount of solid wastes, total flow quantity of scraps, and percentage of materials remanufactured are also some important indicators with relatively high sensitivity. On the other hand, amount of water consumption, quality of air emission and amount of energy consumption were found to be the least important indicators with low sensitivity. The manager of this company can give relatively less focus to these factors without worsening the environmental performance too much. This model can also help a manager to achieve a prespecified level of performance. The model allows a manager to input the required level of environmental performance, and the model will determine at what level each environmental indicator needs to be.

This study makes several theoretical contributions in the field of green supply chains. First, this study identified the key performance indicators that affect the overall environmental performance across the supply chain of an organization. Second, this study proposes a BBN-based framework for the green or environmental performance prediction of a supply chain. The final contribution of this paper is that it investigates how the individual key performance indicators affect the overall environmental performance of a supply chain.

Using this model, managers and executives will be able to understand which performance indicators most affect green supply chain performance of their company. They will also be able to understand which performance indicators to focus on first, and where the resource should be allocated first to achieve the optimum level of environmental performance. As managers usually have limited resources at their disposal, prioritizing and optimizing resource allocation can greatly help in achieving environmental objectives of a supply chain. Using the current performance level of each performance indicator, they will be able to monitor current environmental performance, which will help them to understand the company's current relative position in the industry. Using diagnostic analysis, managers can determine the target performance indicator levels required to achieve satisfactory overall performance.

This study has some limitations. Due to limitations in collecting data, only one company's data has been used to test the model. Another limitation is that not all possible key environmental performance indicators were added to the proposed BBN model. This model only considered two states, namely satisfactory and unsatisfactory states for the BBN nodes.

There are several directions future researches on this topic can take. One direction can be adding more performance indicators. A more comprehensive model validation test can be performed by collecting data from multiple sources and performing multiple case studies. Another direction for future research can be incorporating multiple states instead of just satisfactory and unsatisfactory states, which can be an exciting direction for future research. IoT devices can be used to collect environmental data in real time which can be used as the input for an online algorithm. This algorithm can update the BBN model in real time for monitoring purposes. Other artificial intelligence-based tools such as knowledge systems, fuzzy AHP, or Bayesian Regression Trees can be developed for predicting green supply chain performance and the results can be compared.

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References

1. Gong, R.; Xue, J.; Zhao, L.; Zolotova, O.; Ji, X.; Xu, Y. A Bibliometric Analysis of Green Supply Chain Management Based on the Web of Science (WOS) Platform. *Sustainability* **2019**, *11*, 3459. [CrossRef]
2. Kim, B.; Oh, H. The impact of decision-making sharing between supplier and manufacturer on their collaboration performance. *Supply Chain Manag. Int. J.* **2005**, *10*, 223–236. [CrossRef]
3. Jian, J.; Guo, Y.; Jiang, L.; An, Y.; Su, J. A multi-objective optimization model for green supply chain considering environmental benefits. *Sustainability* **2019**, *11*, 5911. [CrossRef]
4. Hoole, R. Five ways to simplify your supply chain. *Supply Chain Manag. Int. J.* **2005**, *10*, 3–6. [CrossRef]
5. Panchal, G.; Jain, V. A review on select models for supply chain formation. *Int. J. Bus. Perform. Supply Chain Model.* **2011**, *3*, 113. [CrossRef]
6. Panicker, V.V.; Sridharan, R. Modelling supply chain decision problem with fixed charge—A review. *Int. J. Bus. Perform. Supply Chain Model.* **2011**, *3*, 195. [CrossRef]
7. Xing, G.; Xia, B.; Guo, J. Sustainable cooperation in the green supply chain under financial constraints. *Sustainability* **2019**, *11*, 5977. [CrossRef]
8. Sarkis, J. Manufacturing's role in corporate environmental sustainability—Concerns for the new millennium. *Int. J. Oper. Prod. Manag.* **2001**, *21*, 666–686. [CrossRef]
9. Lewis, H.; Gertsakis, J.; Grant, T.; Morelli, N.; Sweatman, A. *Design and Environment: A Global Guide to Designing Greener Goods*; Greenleaf Pub: Austin, TX, USA, 2001; ISBN 1874719438.
10. Bhattacharya, A.; Mohapatra, P.; Kumar, V.; Dey, P.K.; Brady, M.; Tiwari, M.K.; Nudurupati, S.S. Green supply chain performance measurement using fuzzy ANP-based balanced scorecard: A collaborative decision-making approach. *Prod. Plan. Control* **2014**, *25*, 698–714. [CrossRef]
11. Dvorsky, J.; Popp, J.; Virglerova, Z.; Kovács, S.; Oláh, J. Assessing the importance of market risk and its sources in the SME of the Visegrad Group and Serbia. *Adv. Decis. Sci.* **2018**, *22*, 1–22.
12. Oláh, J.; Virglerova, Z.; Popp, J.; Kliestikova, J.; Kovács, S. The Assessment of Non-Financial Risk Sources of SMES in the V4 Countries and Serbia. *Sustainability* **2019**, *11*, 4806. [CrossRef]
13. Oláh, J.; Kovács, S.; Virglerova, Z.; Lakner, Z.; Kovacova, M.; Popp, J. Analysis and Comparison of Economic and Financial Risk Sources in SMEs of the Visegrad Group and Serbia. *Sustainability* **2019**, *11*, 1853. [CrossRef]
14. Srivastava, S.K. Green supply-chain management: A state-of-the-art literature review. *Int. J. Manag. Rev.* **2007**, *9*, 53–80. [CrossRef]
15. Parsaeifar, S.; Bozorgi-Amiri, A.; Naimi-Sadigh, A.; Sangari, M.S. A game theoretical for coordination of pricing, recycling, and green product decisions in the supply chain. *J. Clean. Prod.* **2019**, *226*, 37–49. [CrossRef]
16. Lima-Junior, F.R.; Carpinetti, L.C.R. Predicting supply chain performance based on SCOR®metrics and multilayer perceptron neural networks. *Int. J. Prod. Econ.* **2019**, *212*, 19–38. [CrossRef]
17. Lima-Junior, F.R.; Carpinetti, L.C.R. Quantitative models for supply chain performance evaluation: A literature review. *Comput. Ind. Eng.* **2017**, *113*, 333–346. [CrossRef]
18. Maestrini, V.; Luzzini, D.; Maccarrone, P.; Caniato, F. Supply chain performance measurement systems: A systematic review and research agenda. *Int. J. Prod. Econ.* **2017**, *183*, 299–315. [CrossRef]
19. Mishra, D.; Gunasekaran, A.; Papadopoulos, T.; Hazen, B. Green supply chain performance measures: A review and bibliometric analysis. *Sustain. Prod. Consum.* **2017**, *10*, 85–99. [CrossRef]
20. Gunasekaran, A.; Patel, C.; Tirtiroglu, E. Performance measures and metrics in a supply chain environment. *Int. J. Oper. Prod. Manag.* **2001**, *21*, 71–87. [CrossRef]
21. Hervani, A.A.; Helms, M.M.; Sarkis, J. Performance measurement for green supply chain management. *Benchmarking* **2005**, *12*, 330–353. [CrossRef]
22. Lau, K.H. Benchmarking green logistics performance with a composite index. *Benchmarking* **2011**, *18*, 873–896. [CrossRef]
23. Testa, F.; Iraldo, F. Shadows and lights of GSCM (green supply chain management): Determinants and effects of these practices based on a multi-national study. *J. Clean. Prod.* **2010**, *18*, 953–962. [CrossRef]
24. Wilkerson, T. Can one green deliver another? *Harv. Bus. Rev.* **2005**, 3–4.

25. Cousins, P.D.; Lawson, B.; Petersen, K.J.; Fugate, B. Investigating green supply chain management practices and performance: The moderating roles of supply chain ecocentricity and traceability. *Int. J. Oper. Prod. Manag.* **2019**, *39*, 767–786. [CrossRef]

26. Zhu, W.; He, Y. Green product design in supply chains under competition. *Eur. J. Oper. Res.* **2017**, *258*, 165–180. [CrossRef]

27. Shohan, S.; Ali, S.M.; Kabir, G.; Ahmed, S.K.; Suhi, S.A.; Haque, T. Green supply chain management in the chemical industry: structural framework of drivers. *Int. J. Sustain. Dev. World Ecol.* **2019**, *26*, 752–768. [CrossRef]

28. Yu, W.; Ramanathan, R. An empirical examination of stakeholder pressures, green operations practices and environmental performance. *Int. J. Prod. Res.* **2015**, *53*, 6390–6407. [CrossRef]

29. Uddin, S.; Ali, S.M.; Kabir, G.; Suhi, S.A.; Enayet, R.; Haque, T. An AHP-ELECTRE framework to evaluate barriers to green supply chain management in the leather industry. *Int. J. Sustain. Dev. World Ecol.* **2019**, *26*, 732–751. [CrossRef]

30. Banerjee, M.; Mishra, M. Retail supply chain management practices in India: A business intelligence perspective. *J. Retail. Consum. Serv.* **2017**, *34*, 248–259. [CrossRef]

31. Swami, S.; Shah, J. Channel coordination in green supply chain management. *J. Oper. Res. Soc.* **2013**, *64*, 336–351. [CrossRef]

32. Azevedo, S.G.; Carvalho, H.; Cruz-Machado, V. A proposal of LARG Supply Chain Management Practices and a Performance Measurement System. *Int. J. e-Educ. e-Bus. e-Manag. e-Learn.* **2011**, *1*, 7–14. [CrossRef]

33. Maleki, M.; Machado, V.C. Supply chain performance monitoring using Bayesian network. *Int. J. Bus. Perform. Supply Chain Model.* **2013**, *5*, 177. [CrossRef]

34. Bai, C.; Sarkis, J. Green supplier development: A review and analysis. In *Handbook on the Sustainable Supply Chain*; Edward Elgar Publishing: Chatham, UK, 2019.

35. Vahdani, B.; Mousavi, S.M.; Tavakkoli-Moghaddam, R.; Hashemi, H. A new enhanced support vector model based on general variable neighborhood search algorithm for supplier performance evaluation: A case study. *Int. J. Comput. Intell. Syst.* **2017**, *10*, 293–311. [CrossRef]

36. Beamon, B.M. Measuring supply chain performance. *Int. J. Oper. Prod. Manag.* **1999**, *19*, 275–292. [CrossRef]

37. King, A.A.; Lenox, M.J. Lean and Green? an Empirical Examination of the Relationship Between Lean Production and Environmental Performance. *Prod. Oper. Manag.* **2009**, *10*, 244–256. [CrossRef]

38. Klassen, R.D.; McLaughlin, C.P. The Impact of Environmental Management on Firm Performance. *Manag. Sci.* **1996**, *42*, 1199–1214. [CrossRef]

39. Sarkis, J.; Rasheed, A. Greening the manufacturing function. *Bus. Horiz.* **1995**, *38*, 17–27. [CrossRef]

40. Rehman, M.A.; Seth, D.; Shrivastava, R.L. Impact of green manufacturing practices on organisational performance in Indian context: An empirical study. *J. Clean. Prod.* **2016**, *137*, 427–448. [CrossRef]

41. Vazquez-Brust, D.A.; Campos, L.M.S. Mapping lean manufacturing practices and green manufacturing practices in supply chains. In *Handbook on the Sustainable Supply Chain*; Edward Elgar Publishing: Chatham, UK, 2019; p. 291.

42. Choudhary, K.; Sangwan, K.S. Benchmarking Indian ceramic enterprises based on green supply chain management pressures, practices and performance. *Benchmarking Int. J.* **2018**, *25*, 3628–3653. [CrossRef]

43. Chekima, B.; Wafa, S.A.; Igau, O.A.; Chekima, S.; Sondoh, S.L., Jr. Examining green consumerism motivational drivers: Does premium price and demographics matter to green purchasing? *J. Clean. Prod.* **2016**, *112*, 3436–3450. [CrossRef]

44. Jaiswal, D.; Kant, R. Green purchasing behaviour: A conceptual framework and empirical investigation of Indian consumers. *J. Retail. Consum. Serv.* **2018**, *41*, 60–69. [CrossRef]

45. Faruk, A.C.; Lamming, R.C.; Cousins, P.D.; Bowen, F.E. Analyzing, mapping, and managing environmental impacts along supply chains. *J. Ind. Ecol.* **2002**, *5*, 13–36. [CrossRef]

46. Green, K.W., Jr.; Zelbst, P.J.; Meacham, J.; Bhadauria, V.S. Green supply chain management practices: Impact on performance. *Supply Chain Manag. Int. J.* **2012**, *17*, 290–305. [CrossRef]

47. Tseng, M.-L.; Islam, M.S.; Karia, N.; Fauzi, F.A.; Afrin, S. A literature review on green supply chain management: Trends and future challenges. *Resour. Conserv. Recycl.* **2019**, *141*, 145–162. [CrossRef]

48. Ahi, P.; Searcy, C. An analysis of metrics used to measure performance in green and sustainable supply chains. *J. Clean. Prod.* **2015**, *86*, 360–377. [CrossRef]

49. Keshavarz Ghorabaee, M.; Amiri, M.; Zavadskas, E.K.; Antucheviciene, J. Supplier evaluation and selection in fuzzy environments: A review of MADM approaches. *Econ. Res. Istraživanja* **2017**, *30*, 1073–1118. [CrossRef]

50. Maditati, D.R.; Munim, Z.H.; Schramm, H.-J.; Kummer, S. A review of green supply chain management: From bibliometric analysis to a conceptual framework and future research directions. *Resour. Conserv. Recycl.* **2018**, *139*, 150–162. [CrossRef]

51. Sen, D.K.; Datta, S.; Mahapatra, S.S. Sustainable supplier selection in intuitionistic fuzzy environment: A decision-making perspective. *Benchmarking Int. J.* **2018**, *25*, 545–574. [CrossRef]

52. Kuo, R.J.; Wang, Y.C.; Tien, F.C. Integration of artificial neural network and MADA methods for green supplier selection. *J. Clean. Prod.* **2010**, *18*, 1161–1170. [CrossRef]

53. Yazdani, M.; Chatterjee, P.; Zavadskas, E.K.; Zolfani, S.H. Integrated QFD-MCDM framework for green supplier selection. *J. Clean. Prod.* **2017**, *142*, 3728–3740. [CrossRef]

54. Tang, X.; Wei, G.; Gao, H. Models for multiple attribute decision making with interval-valued pythagorean fuzzy muirhead mean operators and their application to green suppliers selection. *Informatica* **2019**, *30*, 153–186. [CrossRef]

55. Jenssen, M.M.; de Boer, L. Implementing life cycle assessment in green supplier selection: A systematic review and conceptual model. *J. Clean. Prod.* **2019**, *229*, 1198–1210. [CrossRef]

56. Xu, X.-G.; Shi, H.; Cui, F.-B.; Quan, M.-Y. Green Supplier Evaluation and Selection Using Interval 2-Tuple Linguistic Hybrid Aggregation Operators. *Informatica* **2018**, *29*, 801–824. [CrossRef]

57. Handfield, R.; Walton, S.V.; Sroufe, R.; Melnyk, S.A. Applying environmental criteria to supplier assessment: A study in the application of the Analytical Hierarchy Process. *Eur. J. Oper. Res.* **2002**, *141*, 70–87. [CrossRef]

58. Pineda-Henson, R.; Culaba, A.B.; Mendoza, G.A. Evaluating environmental performance of pulp and paper manufacturing using the analytic hierarchy process and life-cycle assessment. *J. Ind. Ecol.* **2002**, *6*, 15–28. [CrossRef]

59. Lin, R.-J.; Chen, R.-H.; Nguyen, T.-H. Green supply chain management performance in automobile manufacturing industry under uncertainty. *Procedia Soc. Behav. Sci.* **2011**, *25*, 233–245. [CrossRef]

60. Rostamzadeh, R.; Govindan, K.; Esmaeili, A.; Sabaghi, M. Application of fuzzy VIKOR for evaluation of green supply chain management practices. *Ecol. Indic.* **2015**, *49*, 188–203. [CrossRef]

61. Gunasekaran, A.; Subramanian, N.; Rahman, S. Green supply chain collaboration and incentives: Current trends and future directions. *Transp. Res. Part E: Logist. Transp. Rev.* **2015**, *74*, 1–10. [CrossRef]

62. Li, Y. Research on the performance measurement of green supply chain management in China. *J. Sustain. Dev.* **2011**, *4*, 101. [CrossRef]

63. Vachon, S. Green supply chain practices and the selection of environmental technologies. *Int. J. Prod. Res.* **2007**, *45*, 4357–4379. [CrossRef]

64. Laosirihongthong, T.; Adebanjo, D.; Choon Tan, K. Green supply chain management practices and performance. *Ind. Manag. Data Syst.* **2013**, *113*, 1088–1109. [CrossRef]

65. Shaw, S.; Grant, D.B.; Mangan, J. Developing environmental supply chain performance measures. *Benchmarking Int. J.* **2010**, *17*, 320–339. [CrossRef]

66. Seman, N.A.A.; Zakuan, N.; Jusoh, A.; Arif, M.S.M.; Saman, M.Z.M. Green supply chain management: A review and research direction. *Int. J. Manag. Value Supply Chains* **2012**, *3*, 1–18. [CrossRef]

67. Zhu, Q.; Sarkis, J.; Geng, Y. Green supply chain management in China: Pressures, practices and performance. *Int. J. Oper. Prod. Manag.* **2005**, *25*, 449–468. [CrossRef]

68. Noci, G. Designing 'green'vendor rating systems for the assessment of a supplier's environmental performance. *Eur. J. Purch. Supply Manag.* **1997**, *3*, 103–114. [CrossRef]

69. Shen, L.; Olfat, L.; Govindan, K.; Khodaverdi, R.; Diabat, A. A fuzzy multi criteria approach for evaluating green supplier's performance in green supply chain with linguistic preferences. *Resour. Conserv. Recycl.* **2013**, *74*, 170–179. [CrossRef]

70. Cucchiella, F.; D'Adamo, I. Issue on supply chain of renewable energy. *Energy Convers. Manag.* **2013**, *76*, 774–780. [CrossRef]

71. Kurien, G.P.; Qureshi, M.N. Performance measurement systems for green supply chains using modified balanced score card and analytical hierarchical process. *Sci. Res. Essays* **2012**, *7*, 3149–3161.

72. Cai, Z.; Sun, S.; Si, S.; Yannou, B. Identifying product failure rate based on a conditional Bayesian network classifier. *Expert Syst. Appl.* **2011**, *38*, 5036–5043. [CrossRef]

73. Abolbashari, M.H.; Chang, E.; Hussain, O.K.; Saberi, M. Smart buyer: A Bayesian network modelling approach for measuring and improving procurement performance in organisations. *Knowl. Based Syst.* **2018**, *142*, 127–148. [CrossRef]

74. Langseth, H.; Portinale, L. Bayesian networks in reliability. *Reliab. Eng. Syst. Saf.* **2007**, *92*, 92–108. [CrossRef]

75. Mahadevan, S.; Zhang, R.; Smith, N. Bayesian networks for system reliability reassessment. *Struct. Saf.* **2001**, *23*, 231–251. [CrossRef]

76. Baesens, B.; Verstraeten, G.; Van den Poel, D.; Egmont-Petersen, M.; Van Kenhove, P.; Vanthienen, J. Bayesian network classifiers for identifying the slope of the customer lifecycle of long-life customers. *Eur. J. Oper. Res.* **2004**, *156*, 508–523. [CrossRef]

77. Abad-Grau, M.M.; Arias-Aranda, D. Operations strategy and flexibility: Modeling with Bayesian classifiers. *Ind. Manag. Data Syst.* **2006**, *106*, 460–484. [CrossRef]

78. Gambelli, D.; Bruschi, V. A Bayesian network to predict the probability of organic farms' exit from the sector: A case study from Marche, Italy. *Comput. Electron. Agric.* **2010**, *71*, 22–31. [CrossRef]

79. Neapolitan, R.E. Learning Bayesian Networks. *Mol. Biol.* **2003**, *6*, 674. [CrossRef]

80. Gopnik, A.; Tenenbaum, J.B. Bayesian networks, Bayesian learning and cognitive development. *Dev. Sci.* **2007**, *10*, 281–287. [CrossRef]

81. Norsys Software Corp. Netica Version 4.16. Canada: Norsys Software Corp. 2014. Available online: www.norsys.com/Accessed (accessed on 15 September 2017).

82. Kabir, G.; Balek, N.B.C.; Tesfamariam, S. Consequence-based framework for buried infrastructure systems: A Bayesian belief network model. *Reliab. Eng. Syst. Saf.* **2018**, *180*, 290–301. [CrossRef]

83. Kabir, G.; Cruz, A.M.; Suda, H.; Tesfamariam, S.; Giraldo, F.M. Earthquake-related Natech risk assessment using a Bayesian belief network model. *Struct. Infrastruct. Eng.* **2019**, 1–15. [CrossRef]