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Bayesian network development and validation for siting selection

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Increased generation of waste, production of plastics, and poor environmental stewardship has led to an increase in floating litter. Significant efforts have been dedicated to mitigating this globally relevant issue. Depending on the location of floating litter, removal methods would vary, but usually include manual cleanups by volunteers or workers, use of heavy machinery to rake or sweep litter off beaches or roads, or passive litter collection traps. In the open ocean or streams, a common passive technique is to use booms and a collection receptacle to trap floating litter. These passive traps are usually installed to intercept floating litter; however, identifying the appropriate locations for installing these collection devices is still not fully investigated. We utilized four common criteria and fifteen sub-criteria to determine the most appropriate setup location for an in-stream collection device (Litter Gitter—Osprey Initiative, LLC, Mobile, AL, USA). Bayesian Network technology was applied to analyze these criteria comprehensively. A case study composed of multiple sites across the U.S. Gulf of Mexico Coast was used to validate the proposed approach, and propagation and sensitivity analyses were used to evaluate performance. The results show that the fifteen summarized criteria combined with the Bayesian Network approach could

aid location selection and have practical potential for in-stream litter collection devices in coastal areas.

DEDICATION

I would like to recognize my parents, my wife, my brothers, my sisters, and my kids for their continuous support and motivation to me. I would like to provide my appreciation and love to my Mother for taking care of my father during his tough time. This is a gift from myself to my father who passed away on Aug 16, 2021.

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CHAPTER I

IN-STREAM MARINE LITTER COLLECTION DEVICE LOCATION DETERMINATION USING BAYESIAN NETWORK

Introduction

Economic development and rapid population growth have led to increasing volumes of waste generation, particularly trash and litter from human daily life and manufacturing activities [1]. Much of this waste eventually enters waterways or water bodies, becoming floating litter. Marine debris (often referred to as marine litter), generally synonymous with floating litter/marine litter, leads to the deaths of many marine organisms [2,3] and millions of dollars of economic losses each year [4,5,6]. Marine litter is an ever-increasing problem with the continuous growth of solid waste generation domestically and globally [7]. Sources of marine litter are ocean-based (e.g., from fishing vessels, stationary platforms, cargo ships, or other vessels) and land-based (e.g., from stormwater discharges, wind, extreme natural events, and waterfront areas such as beaches, piers, harbors, riverbanks, marinas, and docks) [8]. Litter can be found both floating at the surface and sinking to the ocean bed [9]. Among the marine litter distributed worldwide, approximately 82% of marine litter originates from land-based sources [10]. Approximately 275 million metric tons of plastic waste were generated by 192 coastal countries in 2010, with 4.8 to 12.7 million metric tons entering the ocean [7]. Floating litter, in particular, is harmful to the environment, marine life, human health, and the economy. For instance, piles of litter on the shore decrease the aesthetic value of such areas and make them less attractive to local residents and tourists; moreover, ingestion and entanglement caused by marine litter are fatal to marine organisms [11,12,13], and 17% of marine species ingesting/entangled in the litter are listed as near-threatened, vulnerable, endangered, or critically endangered [14]. Non-native species carried by marine litter drifting worldwide pose a major threat to local marine life [15]. For these reasons, there is an urgent need to remove or reduce floating litter in coastal areas to protect and enhance coastal resilience.

In the study area of this research (Northern U.S. Gulf Coast), the primary litter commonly found is plastic, particularly single-use plastic, originating from land-based litter [16]. According to a recent marine litter study, less than 10% of local residents in the Mississippi Gulf Coast region would prefer to visit Mississippi or Louisiana beaches; 54% of beach visitors complain about the water and shoreline quality [17]. Depending on its location, there are generally two ways to remove macro-floating litter: (1) litter in the ocean, using collection vessels/tools to collect; and (2) litter in coastal streams and rivers, using collection traps [15,18,19,20]. Compared with litter in the ocean, transitory stream and river litter are easier to remove as their trajectory is within a predetermined path and can be collected using stationary traps. There are several different in-stream litter collection devices available to rent or purchase that have been used extensively in inland streams; however, most operate similarly. Each typically includes floating booms that guide or collect floating litter, with some containing a centralized receptacle. Although floating in-stream litter collection devices are effective tools, it is necessary to place them systematically in order to yield the most benefit and avoid inefficiencies in collection capabilities due to a lack of systematic installation. Therefore, the selection of installation locations for such devices is critical. Identifying optimal locations for these devices involves multiple factors pertaining to stream hydrology and cost. Given the complexity and multiple siting consideration factors for an in-stream litter collection device, this process can be considered a Multiple Criteria Decision Making (MCDM) problem.

A wide set of MCDM methods, including Analytic Hierarchy Process (AHP), weighted sum approach (SW), multi-attribute value function theory (MAVT), multi-attribute utility function theory (MAUT), analytic network process (ANP), elimination and choice expressing reality (ELECTRE), and the TOPSIS method, can be used to determine the most appropriate location(s). Generally, in most multi-criteria problems, there is no optimal solution that can satisfy all the criteria at the same time; therefore, compromise solutions must be found [21]. MCDM has been used in many selection-related applications, such as supplier selection and order allocation (e.g., [22]), transportation systems [23], material selection (e.g., [24]), employee recruiting (e.g., [25]), sustainable project portfolio selection (e.g., [26]), and manufacturing (e.g., [27]). Among these approaches, TOPSIS, presented by Hwang and Yoon (1981), has become one of the most widely accepted MCDM approaches [28]. TOPSIS enables decision makers to decide among a group of key parameters that maximize the ability to satisfy the stakeholders [21].

Location selection problems involve variability and subjectivity, which require the understanding of overall available information via space and time scales. A statistical modeling approach to handle uncertainty and make detailed, rational, and transparent contingency plans before taking action is needed. One of the most popular methods for integrating this complexity into tangible actions is Bayesian Network (BN). BN decision making is a widely used tool in location selection applications, such as selecting the most sustainable and economical charging stations for electric vehicles [29]. In Singapore, BN is used to decide bridge location to help the land transport authority properly select and optimize optimal bridge locations [30]. A study in southeastern Australia implemented BN theory in a wildfire location selection problem to choose fire station locations with the least cost impact [31]. BN has also been used to facilitate optimal blood logistics network decisions with the consideration of natural disasters [32]. More recently, BN was utilized to evaluate whether the industry needs to adapt additive manufacturing and model and assess the sustainability performance of supply chain networks [33,34]. Given the potential of the BN approach, it holds the capability to be applied to the decision-making process associated with siting in-stream litter collection devices.

In light of the current state of the art, the major contributions of this study over the existing literature are as follows:

- This is the first study to methodologically identify and prioritize in-stream litter collection device installation sites.
- A BN approach is proposed to determine suitable in-stream litter collection device installation sites based on four criteria and fifteen sub-criteria identified in this study.
- Litter collection device locations across the Northern U.S. Gulf Coast have been used to validate the proposed approach.

Problem Description and Methodological Framework

Tested In-Stream Litter Collection Device—Litter Gitter

The device used in this study is the Litter Gitter, an innovative device for in-stream litter collection with similar characteristics to other comparable devices used globally, such as The Bandalong Bandit, The Water Goat, Trash Trout, and Sungai Watch's floating Barriers. The Litter Gitter (LG) is a small in-stream collection device developed by Osprey Initiative, LLC, and is designed to intercept floating litter from stormwater runoff. It includes floating booms that use the current to guide trash to a large wire-mesh collection container (shown in **Figure 1**). The boom system does not have any nets or barriers that suspend through the water column; thus, limited harm will be made to fish and other wildlife. Litter Gitters have been used widely (43 currently deployed throughout the U.S.) in inland streams to capture floating litter.

Figure 1 Litter Gitter in Auguste Bayou, Biloxi, Mississippi

Bayesian Network (BN)

Bayesian Network (BN), also referred to as a belief network, is utilized for risk assessment and decision making. BN is a probabilistic model built by an expert based on the theory of Bayes. BN is a useful and efficient approach for calculating the prior probability distribution of undiscovered variables that depend on prior observed variables. A BN model, also called a directed graph, involves two major entities: nodes indicating variables and arrows indicating the interrelationship between nodes. Nodes in BN can be categorized into three classes: (i) parent nodes that do not depend on prior nodes; (ii) child nodes that depend on prior nodes (also referred to as their parent nods); and (iii) intermediate nodes that have both parent and child nodes. In addition, every node in BN has a table referred to as a node probability table (NPT). The base probability of a set of variables can be reconstructed if BN has a different set of evidence. Arrows in a BN denote the connections among nodes, and it can be explained by the conditional probability distribution provided by expert knowledge [35].

Through these relationships, experts can use inference on the random variables in the graph via directed arrows. BN is a distinctive tool for calculating new variable probability distribution computations with unknown conditional spotted variables. With BN, both quantitative and qualitative data can be utilized and added to the model for conditional probability calculation. The constructed nodes can take Boolean (yes/no), integer, qualitative (high/medium/low), discrete, or continuous values. BN has the capability to work with nodes of different types, which is considered as one of the main advantages of using this method. The collected data for the nodes are assembled from historical data and expert standpoints [29]. In this study, BN supports experts and decision makers to evaluate all possible options to locate Litter Gitter sites.

Figure 2 illustrates the BN model with six nodes: N_1, N_2, N_3, N_4, N_5, and N_6, where N_1, N_2, and N_3 are parent nodes. They are initial nodes, so they do not depend on the prior variables, while N_4 and N_5 are intermediate nodes. N_4 depends on N_1, and N_5 depends on N_2 and N_3. N_6 is a child or leaf node, and it depends on both N_4 and N_5. Observation reveals the arrow coming out N_1 to N_4, which indicates that N_1 is an independent node, while N_4 depends on N_1. Equation (1) represents a comprehensive full joint probability distribution of a BN involving n variables: N_1, …, N_n.

$$\mathrm{P(N1, N2,, N3 \ldots. Nn) = P(N1|N2, \ldots. Nn)P(N2|N3, \ldots. Nn)P(N3|N4, \ldots. Nn) \ldots}$$
$$\mathrm{P(Nn-1|\ Nn)\ P(Nn){=}\prod i{=}P(Ni|Ni{+}1,\ldots.,Nn)} \tag{1}$$

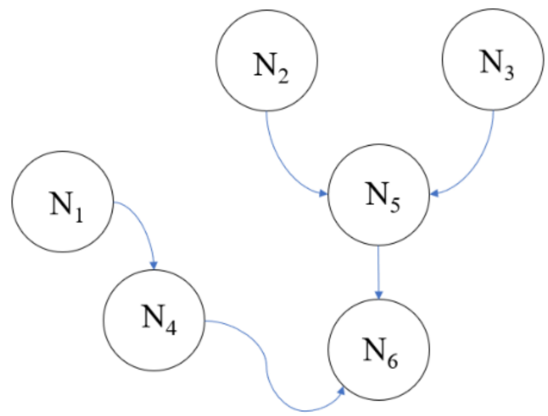


Figure 2 Illustration of Bayesian Network model with six nodes.

The six variables shown in **Figure 2**, N1, N2, N3, N4, N5, and N6 in Equation (1) can be simplified because the primary node of each node is known. For example, we recognize that N4 has exactly one primary node, N1. Thus, the joint probability distribution of P(N1,…. Nn) can be replaced with P(N4| N1), given that only N1 has a significant contribution to the existence of N4. The balanced joint probability distribution variables are delivered in Equation (2).

$$P(N1, N2, N3 \dots, N6) = P(N1)P(N2)\,P(N3)P(N4|N1)P(N5|N2, N3)P(N6|N4, N5) \qquad (2)$$

In Equation (2), we show the first requirement, which is the calculation of the unconditional probability of $P(N_1)$,$P(N_2)$, and $P(N_3)$ and then the conditional probability of $P(N_4|N_1)P(N_5|N_2,N_3)$, and $P(N_6|N_4,N_5)$ to express the joint distribution of $P(N_1,N_2,N_3\ldots,N_6)$.

BN is able to update propagation belief or marginal probabilities. Propagation belief can be added to *P(Ni)* after witnessing another node's performance by observing other variables. The observed variables are referred to as evidence. For example, the conditional probability for variable N_6 given evidence e, (e = {N_1, N_2, N_3, N_4, N_5, N_6}), can be calculated as follows [36]:

$$\begin{aligned} P(N4|e) &= P(N1,\ N2,\ N3,\ N4,\ N5,\ N6)/P(N1,\ N2,\ N3,\ N5,\ N6) \\ &= P(N1,\ N2,\ N3,\ N4,\ N5,\ N6)/\sum N4(N1,\ N2,\ N3,\ N5,\ N6) \end{aligned} \tag{3}$$

The comprehensive conditional probability, represented in Equation (3), can be computed more precisely by discovering conditional self-sufficiency, as mentioned in Equation (4).

$$\begin{aligned} &P(N6|e) = P(N4|N1)P(N5|N2,\ N3)\ P(N6|N4,\ N5) \\ &/\sum N6P(N4|N1)P(N5|N2,\ N3)P(N6|N4,\ N5) \end{aligned} \tag{4}$$

Conjoint Criteria Utilized for Assessing Litter Gitter Site Selection

Criteria assessment plays a significant role in the site selection of an LG with the continuous growth of solid waste generated in water-based environments. Therefore, in this study, the criteria assessment of LG contributing to the site selection focuses on technical, economical, and environmental perspectives. These perspectives are considered to ensure the suitability and safety of the LG and crew members. The sub-criteria connected with suitability and technical criteria were determined by the following procedure. Firstly, the academic literature and feasibility research studies related to marine litter were collected and evaluated, and the initial sub-criteria were constructed accordingly. Secondly, the expert opinions were merged in the scopes of marine litter. Lastly, the less critical sub-criteria were cast off. **Figure 3** illustrates the criteria and sub-criteria considered for site selection of the Litter Gitter. The details of the sub-criteria are addressed below.

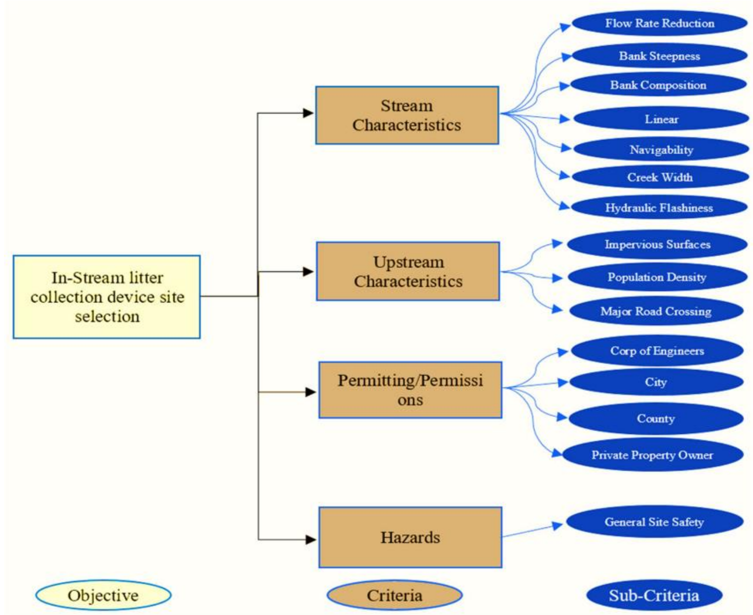


Figure 3 Criteria and sub-criteria for evaluating LG site selection.

Stream Characteristic

Seven sub-criteria, namely, flow rate reduction, bank steepness, bank composition, linear, navigability, creek width, and hydrologic flashness, are considered for the stream characteristic criteria. These criteria were developed during numerous interviews with the owner of Osprey Initiative, LLC, who developed Litter Gitter. The noted criteria come from first-hand experience of installing the Litter Gitters in a variety of environments and geographical locations.

- Flow Rate Reduction: The LG should be placed downstream of a drop. A drop in power usually occurs when a stream straightens out, is downstream of a significant elevation change (i.e., a waterfall), or widens out. This will allow the water to flow smoothly and booms to sit correctly in the water.

- Bank Steepness: When banks are too steep, the booms attached to the LG do not lay correctly and can cause gaps that allow trash to bypass the trap. This gap occurs near the edge of the bank.
- Bank Composition: The preferred method for securing an LG is to use a tree on either side of the stream. If a tree is not available, metal t-stakes could be used.
- Linear: Traps should be placed in the straightest portion of the stream. Putting the trap in a turn/curve could cause the water to flow nonlinearly and allow trash to accumulate on the sides of the LG, leading to escape.
- Navigability: This sub-criterion refers to navigable waterways. These waterways are used for ship movement. Hence, navigable waterways are not appropriate for LG. Navigable waters that are found in the U.S. refer to waters that are subject to tidal flow, and may be used, are reported as used in the past, or may in the future be used for transport that is either interstate or foreign commerce [37].
- Creek Width: Streams between 20 and 40 ft are best suited for LG. Larger streams tend to have high flow capacity, which puts a strain on the boom system used to anchor the LG. Additionally, larger streams can carry natural debris items such as logs or trees. These large debris items can put more tension on the boom system, causing them to break free from the LG, thus causing the trap to malfunction.
- Hydrologic Flashness: Flashness refers to the frequency with which rapid, short-term changes in streamflow occur, especially during events where there is runoff and significant rain. An ideal LG placement would be in a stream that does not have significant flashes (10 ft or less). Sudden changes in water flow can cause extra tension to be placed on the anchor points for the LG.

Upstream Characteristics

The three sub-criteria considered for the upstream characteristics are impervious surfaces, population density, and major road crossings. The following criteria are also based on interviews with staff from Osprey Initiative, LLC, and their field experience. There is a lack of data and literature surrounding sources of upstream litter and more research is needed to support these claims.

- Impervious Surfaces: Can cause runoff, which can carry trash into stream systems. Ideally, the LG could be placed downstream of an area that will have high impervious surfaces. Examples include placing the trap downstream of a shopping center rather than upstream before the shopping center. Successful sites for LG may be placed within 0.25 miles of high-intensity developed areas.
- Population Density: Places with high population density are likely to generate more trash simply because more people are there. Ideally, the LG will be located downstream of an area with high population density.
- Major Road Crossings: A considerable amount of littering occurs around major road crossings. Ideally, the LG should be placed downstream of the road crossings to collect the litter coming from these road crossings.

Permissions and Permitting

In order to install an LG, a set of permissions or permits are typically required. These permissions could include the U.S. Army Corps of Engineers, city, county, or private property owners. During pre-site selection visits, assessments of the likelihood of receiving permission or permits are considered. These considerations include noting the presence of endangered species or habitats that are sensitive to disturbances, such as nesting grounds. Additionally, the jurisdiction in which the site falls under must be investigated in order to infer the practicality of receiving the appropriate permits within the project timeline.

Hazards

Site safety is important to provide the crew with a secure environment to install and maintain the LGs. A site associated with potential risks is subject to exclusion. On the contrary, the safest site has more priority for selection. If the site receives a high risk rating, the trap cannot be placed at this location. Some examples of things that would increase a sites hazard rating could include a steep entrance to the creek, dangerous parking options, and the continual presence of dangerous animals.

The Bayesian Network (BN) Methodological Framework

Figure 4 systematically illustrates the BN methodological framework used to evaluate an LG site selection problem, more specific to a coastal application. The framework delineates the steps that could be undertaken to reliably validate the LG site selection decisions. Essentially, the framework is classified into the following three stages:

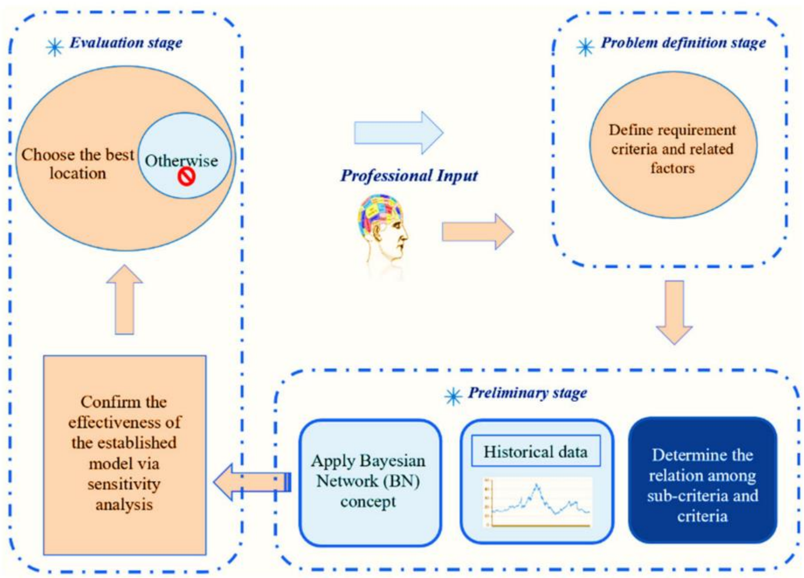


Figure 4 Methodology framework for evaluating an LG site selection problem.

- **Problem definition and systematic study**: Systematically identifies the necessary criteria and sub-criteria required to site an LG for collecting marine litter in a coastal area. Professional input, accessible literature, and elementary LG installation procedures, as instructed by the Environmental Protection Agency (EPA), the U.S. Army Corps of Engineers (USACE), and the National Oceanic Atmospheric Administration (NOAA) [3,4], were utilized to create the criteria and sub-criteria. Overall, four criteria and fifteen sub-criteria are identified to evaluate a possible site for installing the LG (see **Figure 3**).
- **The preliminary stage**: Includes collecting data, formulating, and modeling stages. A suitable link between the criteria and sub-criteria is constructed. Related data are gathered to build the BN model with the information collected via the first stage, and a BN model is constructed for each potential site.
- **Evaluating stage**: Used to check the reliability and validity of the LG project. The result of the BN will undergo sensitivity analyses during the evaluating stage. If authenticated,

the analyst will select the best LG site(s); if not, the first stage will be revised, and the criteria/sub-criteria selection and data collection processes will be reevaluated. The process will continue until each site is validated correctly via sensitivity analysis.

Floating Litter Case Study Solution

BN Model for Evaluating Candidate Litter Gitter Sites

More than fifty sites in the U.S. were initially studied. Ten candidate sites in the coastal area in the south of the U.S. were finally chosen based on their potential success to potentially install LGs. **Figure 5** visualizes the ten candidate sites. The specific locations of the candidate sites are listed in **Table 1**. These potential locations have a common characteristic to ensure initial successful scenarios. For instance, permitting or permission criteria from the city governorate are mandatory for installing such a project. The model takes these criteria as a base requirement for the project. This section shows a BN model using Agena Risk (https://www.agenarisk.com, accessed on 31 March 2022) software for evaluating the possible location of the LG.

Figure 5 The general geographical locations of the ten candidate LG installation sites.

Table 1	The potential LG sites in the coastal area

Site	City	State	Location name	LG Location	
				Latitude	Longitude
1	Mobile	AL	DR-Eslava Sage	30.67321	-88.11316
2	Mobile	AL	3MC-1MC Lawrence	30.70263	-88.05416
3	Daphne	AL1	DO-D'Olive Creek US98	30.65274	-87.91149
4	Ponchatoula	LA2	LP-Ponchatoula Creek_I-55	30.45581	-90.47149
5	Foley	AL	BS-UTBS Cedar	30.38675	-87.69209
6	Biloxi	MS3	BBB-Keegan Bayou_I-110	30.40612	-88.89473
7	Mobile	AL	DR-Montlimar Canal Michael Blvd	30.66329	-88.13669
8	Mobile	AL	3MC-3MC Infirmary	30.69957	-88.07901
9	Mobile	AL	3MC-3MC_Langan Park	30.70562	-88.16482
10	Hammond	LA	LP-Yellow Water River, Adams Rd	30.45864	-90.50564

The proposed model was developed using the BN theory. There are four criteria in the proposed model: (i) stream characteristics, (ii) upstream characteristics, (iii) permitting or permission, and (iv) hazards criteria. Based on a professional's input and literature review, the priority ranking of these criteria is as follows. Permitting or permission (of city, counties, or municipality) is considered the top priority, as permission is mandatory for the project. If permission cannot be granted, the trap cannot be placed at the suggested location. The stream characteristics are considered the second priority since it covers the technical parts of the LG trap project. Without ensuring the availability of all needed requirements, an LG trap cannot be placed. The stream characteristics sub-criterion covers technical parameters that affect crew safety and are considered essential for placing an LG trap. Among all other criteria, the third priority is the upstream characteristics that cover an LG's potential trash capacity and economic criteria.

Below, we provide a description of how different variables are modeled and contribute to the Bayesian Network methodology.

Modeling of Stream Characteristic

Stream characteristics include types of variables that contribute to LG technical stability. **Table 2** shows how the different variables are modeled under the stream characteristics. An explanation behind modeling the variables is further given in **Table 2**. Boolean (for binary decisions (e.g., true/false)) or Truncated Normal (TNORM) distribution (continuous values) are used to model the variables of specific nodes of the BN introduced in **Figure 3**.

Table 2 Modeling of variables contributed to the stream characteristics

Variable	Modeling Procedure	Explanation
Flow Rate Reduction	IF (Flow rate = 1, "True", "False")	It is difficult to position the LG in the direction of rapid rivers. High flow will cause the trash to get out of the LG. Therefore, LG needs to be placed in a downstream drop of energy. In the model, one represents a stable location, and zero represents a disturbance location.
Bank Steepness	TNORM (μ=57, σ2= 33, LB=10, UB= 90)	According to the historical data, bank steepness follows a truncated normal distribution with a mean of 57.
Bank Composition	IF (Bank composition = 1, "True", "False")	As it's described earlier, the bank composition must hold to either a tree or a metal fence t-stakes. If not, the trap cannot be placed.
Linear	IF (Traps linearity = 1, "True", "False")	Linearity is another critical aspect that follows a Boolean distribution. It has an equal probability of finding it or not. The threshold that traps linearity must be equal to one.
Navigability	IF (Navigability =1,"True","False")	Navigability is an essential aspect of LG installation. The if condition ensures no navigability in the intended area. The one indicated area has no navigability. The area is calm enough for the trap to be placed.

Table 2 (continued)

Creek Width Calculation of Creek Width	TNORM (μ= 35, σ2= 12, LB= 10, UB= 50) IF(Creek width <31,"True","False")	According to the collected data, the creek width follows truncated normal distribution with an average of 35. To ensure Trap's safe operation, we want to provide less interruption to the LG. Thus, it preferred the creek width be less than 31.
Hydrologic Flashness	IF (Hydraulic Flashiness <9.0,"True","False")	The greatest accepted safe operation of HF is 9ft.

Modeling of Upstream Characteristics

Three variables contribute to the upstream characteristics of the LG installation, namely, impervious surfaces, population density, and major road crossings. **Table 3** shows how the different variables are modeled under the upstream characteristics. An explanation behind modeling the variables is further given in **Table 3**.

Table 3 Modeling of variables contributed to the upstream characteristics

Variable Name	Modeling Procedure	Explanation
Impervious Surfaces	NORM(μ=0.25, σ2= 0.03)	Impervious surfaces follow a normal distribution with a mean of 0.25 miles and a variance of 0.03.
Population Density Setup Population Density Calculation	TNORM (μ= 2,193, σ2= 1,045, LB= 647, UB= 4,160) IF(Population Density Setup >1,800, "True", "False")	The Population density follows a truncated normal distribution with an average of 2,193 and variance 1,045, the lower bound is 647, and the upper bound is 4,160. As it's explained earlier, a site with a high-density level would be more favorable since the trap will capture more trash. A site would be more useful if the population density level is more than 1,800.

Table 3 (Continued)

Major Road Crossings	IF(Major Road Crossing >1, "True", "False")	As described earlier, more trash occurs in major road crossings. The if condition gives sites located near major road crossings more weight than other sites that don't have.

Modeling of Permissions Approval

For Permission modeling, the IF condition is used to ensure at least one approval is obtained from either corps of engineers, city principle, county principle, or private property owner (see **Figure 6**).

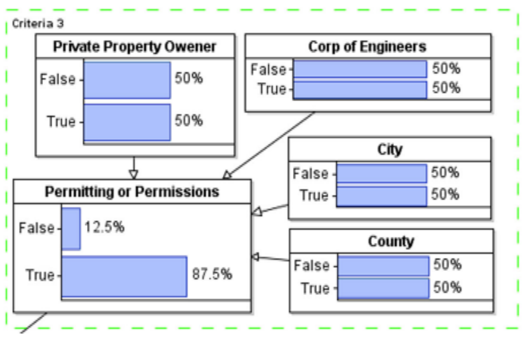


Figure 6 Securing permission modeling from city/county governor.

Modeling of Hazards Criteria

The hazard node was calculated manually based on the information provided from original data provided by Osprey. The selected sites were ranked from low to high based on factors that would impact the safety of the crew while installing and maintaining the LG (see **Figure 7**).

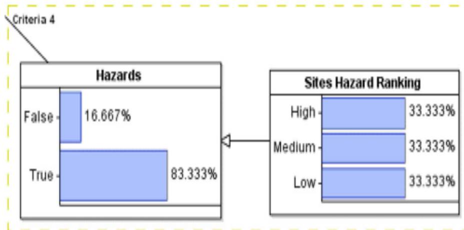


Figure 7 Modeling the hazards variable.

Probability of Site Selection

Table 4 provides the LG site selection probability of the ten candidate sites in the coastal area near the Gulf of Mexico (see **Figure 5** and **Table 1** for the details about the location of the candidate sites). We used the methodological framework introduced in **Figure 4** to evaluate the site selection probability for all the ten candidate sites. The target node for our BN framework is the probability of the LG site selection, which is conditioned based on a set of problem-specific criteria, such as stream characteristics, upstream characteristics, permitting/permission, and hazard criteria. The first selection that stood out to install an LG from the ten candidate sites was Site #7, which is located in Mobile, AL (see **Table 4**). The probability of selecting this site is 81.8% (see **Figure 8**). This site satisfied all the critical installation criteria and other necessary sub-criteria. The second selection site, with a probability of ~76%, is in Mobile City, AL (Site #1). **Figure 9** visualizes the BN results for this site. One of the reasons for placing Site #1 as a second candidate LG installation location over Site #7 is probably the size of the population, which is slightly smaller in Site #7 than Site #1. Furthermore, hydrologic flashiness is slightly less in this selection than in the first selection. Similarly, we demonstrated the BN results for the third-, fourth-, and fifth-best locations, which are nearly 73% (Site #8), 72% (Site #6), and 68% (Site #9), respectively (see **Figure 10, Figure 11 and Figure 12**). Note that the BN results for all the top sites can be compared with the standard BN results shown in **Figure A1** in Appendix A1

Table 4 Site selection probability of the ten candidate sites in the coastal area near the Gulf of Mexico

Criteria	Sub-criteria	Site 1	Site 2	Site 3	Site 4	Site 5	Site 6	Site 7	Site 8	Site 9	Site 10
Stream Characteristics	Flow Rate Reduction	Y*	N*	N	Y	N	N	N	N	N	N
	Bake Steepness	30	90	10	90	60	45	70	45	30	30
	Bank Composition	Tposts	Trees	Trees	Trees/Tposts	Trees	Trees/Tposts	Tposts	Tposts	Tposts	Tposts
	Linear	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
	Navigability	NN	NN	NN	NN	NN	NN	NN	NN	NN	NN
	Creek Width	35ft	20ft	50ft	35ft	10ft	40ft	25ft	20ft	15ft	35ft
	Hydraulic Flashiness	10ft	5ft	3ft	10ft	3ft	2ft	5ft	1ft	3ft	6ft
Upstream Characteristics	Impervious Surfaces	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
	Population Density	2584	1832	1986	983	646	1210	4092	2009	1226	119
	Major Road Crossings	Y	Y	N	Y	N	Y	Y	N	N	N
Permitting/Permissions	Corp of Engineers	Y	Y	N	N	N	Y	Y	Y	Y	N
	City	N	N	Y	N	Y	Y	Y	Y	Y	N
	County	N	N	N	Y	N	N	N	N	N	Y
	Private Property Owner	N	N	N	Y	N	N	N	N	N	N
Hazards	General Site Safety	L*	H*	M*	M	H	L	L	L	L	L
Probability of site selection-True (%)		75.6	50.6	63.4	55.1	43.2	71.9	81.8	73.4	68.2	58.8

*Y-Yes; N-No; H-High; M-medium; L-Low; NN-Non-navigable

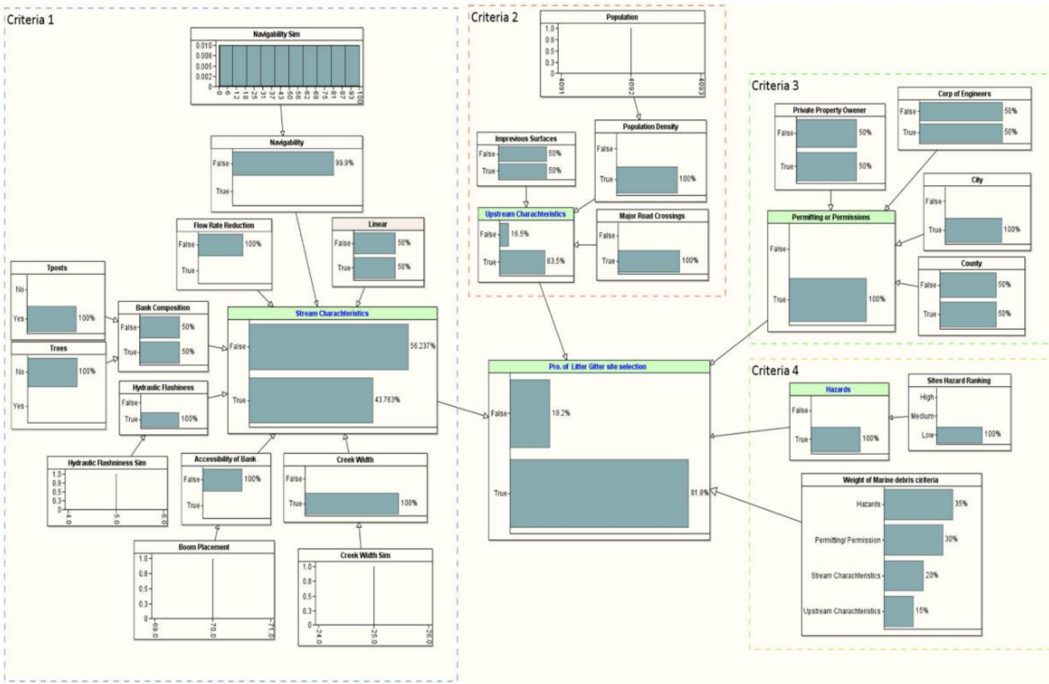


Figure 8 The developed BN model for the first LG selection (Site #7).

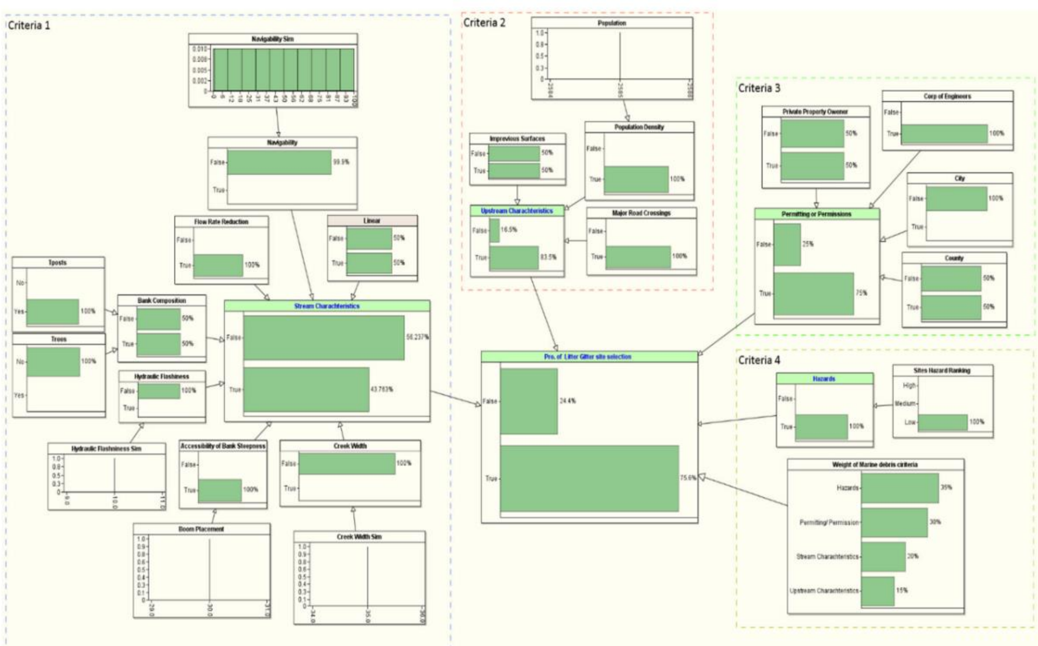


Figure 9 The developed BN model for the second LG selection (Site #1).

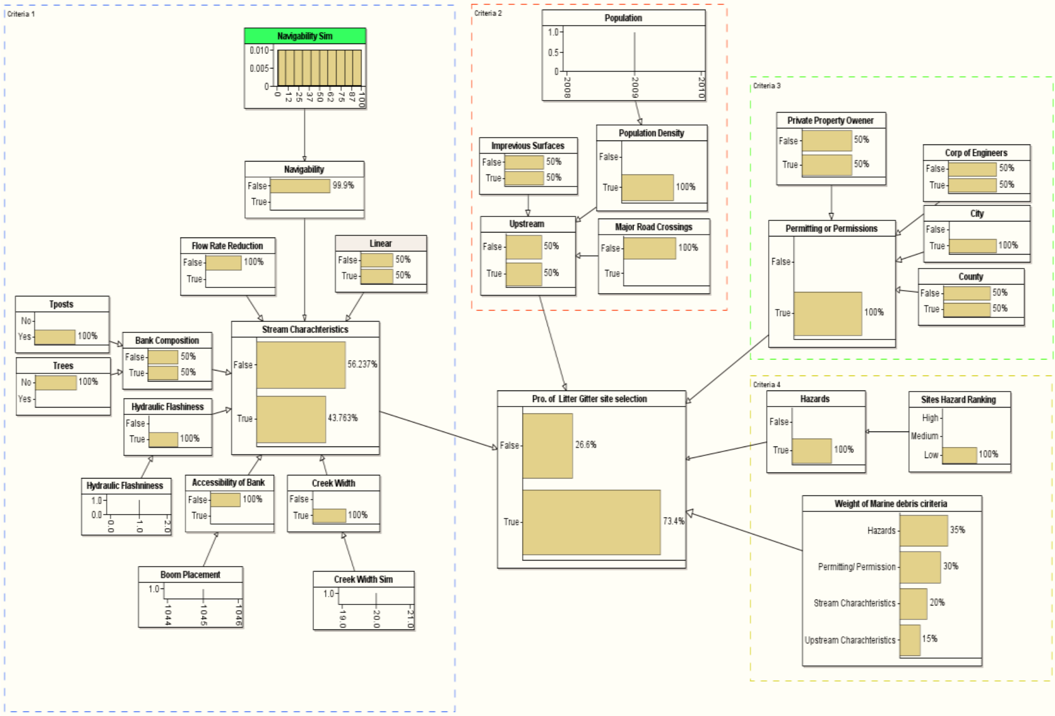


Figure 10 The developed BN model for the third LG selection (Site #8).

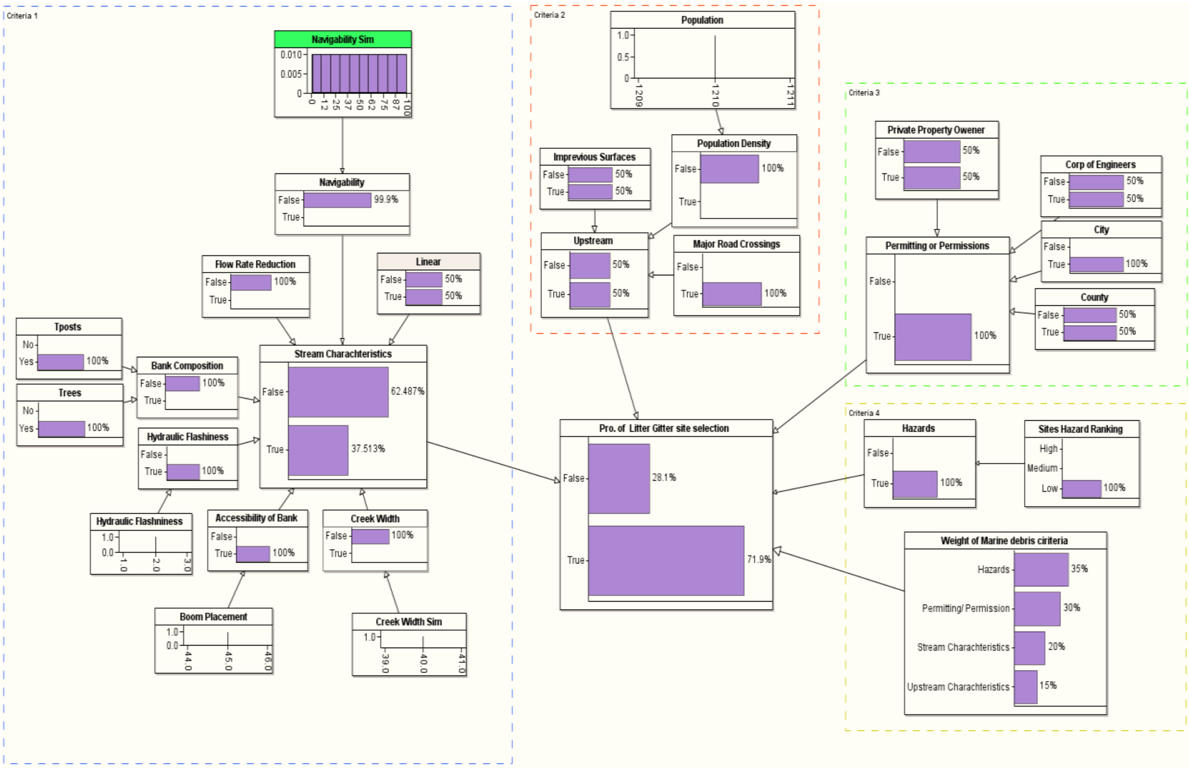


Figure 11 The developed BN model for the fourth LG selection (Site #6).

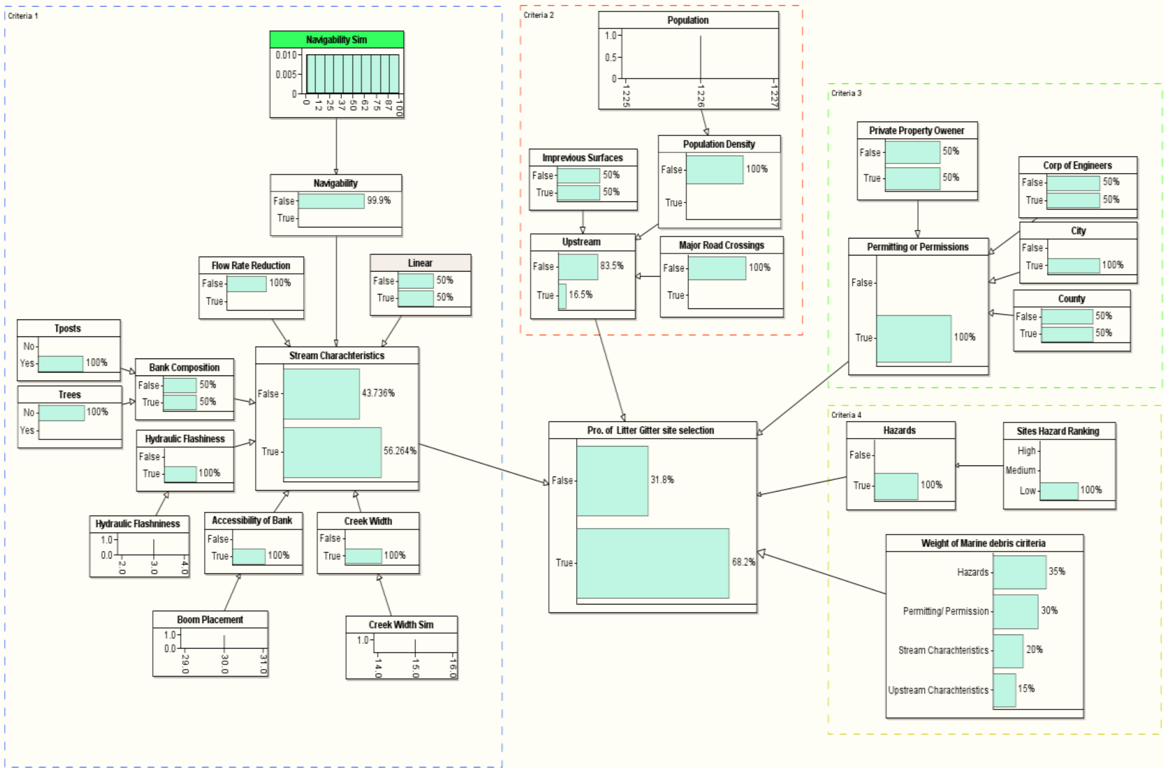


Figure 12 The BN model for the fifth LG selection (Site #9).

Sensitivity Analysis

Sensitivity analysis is a method used to validate the constructed Bayesian Network model that investigates the effect of variables on the target node. Sensitive parameters may significantly affect the results of the target node. Analyzing these parameters may help experts direct their efforts more efficiently to obtain a trustworthy Bayesian Network model.

Validation is utilized to compare the current constructed model to the actual result. In **Figure 13** and **Figure 14**, tornado graphs are used to demonstrate the importance of the nodes in determining the probability of selecting a candidate LG site. The variables in the chart are represented in boxes with two conditions, "true" and "false." The longer the box, the greater the influence on determining the probability of the candidate LG sites (target node). The tornado graph shows hazards, permitting, upstream characteristics, and stream characteristics criteria with a rough difference of 0.25. The analysis of the tornado chart indicates different influences among all criteria. Therefore, we can say that there is a similar influence on the target node among all criteria.

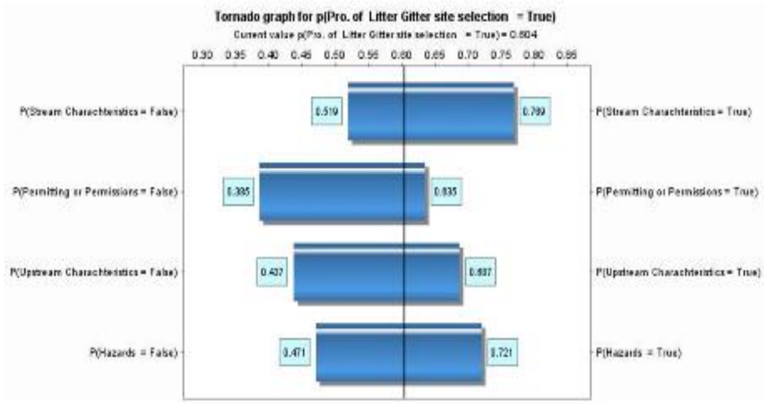


Figure 13 The tornado chart shows the nodes that have the most impact on selecting the first site, “true”.

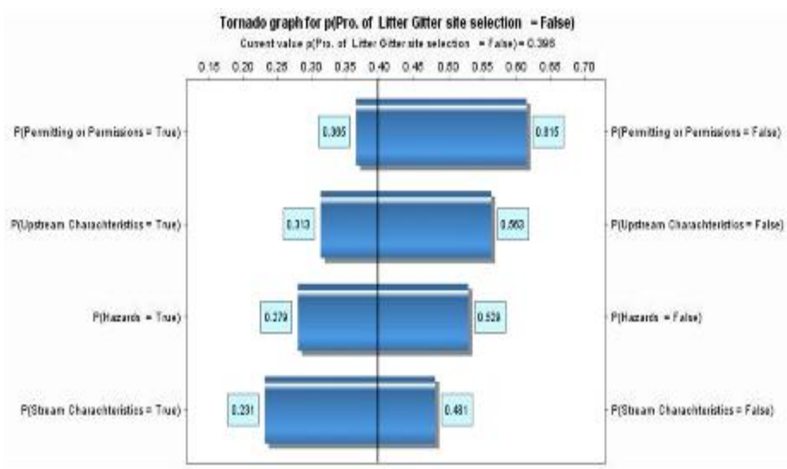


Figure 14 The tornado chart shows the nodes that have the most impact on selecting the first site, “false”

Hazard in the tornado graph explains that the probability of selecting the first LG location (“true”) starts from 0.47 (when the hazard criteria is “false”) to 0.72 (when a hazard criterion is “true”). The probability of selecting the first litter location is 0.6, given that the hazard criteria is achieved. This range (0.47–0.72) is precisely the bar in the tornado graph explained in **Figure 13**. For permitting criteria, upstream characteristics, and stream characteristics criteria, the probability of selecting the first LG location is 0.39–0.64, 0.44–0.69, and 0.52–0.77, respectively.

The chart’s vertical line mainly indicates the marginal probability for the first selection LG location being “true” (0.60). The likelihood of selecting the first selection site location is less sensitive to the changes in our model since all criteria length differences are almost the same between all constructed criteria. Therefore, decision makers must give equal attention to all criteria [29].

Conclusions

Floating litter is one of the most widespread threats that can negatively impact the quality of life in coastal areas. In this study, we developed a methodological framework to assess optimal locations to install an LG, an example of an in-stream litter collection device that has the capability to reduce the quantities of floating litter in local habitats. We identified four criteria and fifteen sub-criteria to determine the most appropriate location to install an LG. The criteria and sub-criteria were incorporated under the BN framework to quantify the selection probability of a site among a set of candidate sites. The developed BN model combines both qualitative and quantitative input for each potential site location. The Northern Gulf of Mexico Coast in the U.S. was used as a case study to validate the BN framework for installing LGs and similar collection devices. All the candidate sites were assessed based on the consideration of the site’s technical and safety factors. We performed a sensitivity analysis to understand the contribution of each criterion for determining the LG site. We found that the contribution of the criteria is ranked as recommended from an expert team and research studies (hazard, permitting, stream characteristics, and upstream characteristics). However, decision makers must place equal focus on all criteria. The proposed BN decision-making framework and the generated insights have the potential to help stakeholders select the most effective sites for in-stream collection devices such as the LG.

CHAPTER II

DEVELOPMENT OF A BAYESIAN NETWORK MODEL FOR BIOMASS-BASED COMBINED HEAT AND POWER SYSTEM SITE SELECTION IN RURAL COMMUNITY

Introduction

Based on the Energy Information Administration (EIA) approximated an increase of demand for Electricity to 4950 billion kilowatt-hours (kWh) by 2040 from 3830 billion kilowatt-hours (kWh) in 2012. Therefore, it requires considerable effort to improve the overall system's energy efficacy [37]. Among multiple energy alternatives, Electricity generated from biomass is a fast-growing renewable energy system because carbon dioxide is seized once the biomass crop is produced. As per the U.S Department of energy, biomass provides approximately billions of tons and has the advantage of producing 1 billion tons by 2040 to satisfy the energy demand [38]. The government is subsidizing domestic fuel prices, which reduces the cost of electricity generation from conventional sources to less than the cost of electricity generation from renewable sources. This support could be backed off with the increase in the population over the years. Therefore, combined heat and power plants powered by biomass (bCHP) can meet rural communities' heating and electrical necessities with less and efficient cost.

Moreover, the bCHP incorporated microgrid has already proven its ability to reduce carbon dioxide ($CO2$) emissions and help increase energy efficiency for structures. Bioenergy scholars in many research aim to increase more ways to use biomass energy to reduce the draining of fossil fuel energy sources to reduce environmental pollution. bCHP has the prospects for improving the current system via reducing pollution and reducing agricultural and forest firewood waste. A more specific aspect of installing bCHP in a rural community is to provide more sustainability and steady energy. Also, bCHP contributes to global warming improvement by reducing anthropogenic as an alternative to fossil fuel [39]. Thus, renewable energy progress would be necessary by 2040 despite some limitations in the affordability of biomass and other valuable alternatives to traditional electricity and other energy sources.

Literature review

In the existing body of literature on bioenergy, the scholars aim to increase more ways to use biomass energy to reduce the consumption of fossil fuel energy sources to reduce environmental pollution. The electricity production from biomass can significantly impact the environment during the conversion. Combined heat and power-based biomass need to meet local and global requirements. Therefore, emissions, solid ash disposal, noise, and other factors must be calculated carefully.

Zhang and Kang [40] studied the distribution density of biomass CHP plants and their heat energy utilization efficiency. They studied the Biomass CHP technology location based on the heat that occurred from the system. They determined that the heat transmission threshold between towns and villages involves heat efficiency usage. They involve the population of town to approximate heat and electricity demand. They referred to the Geographical Information System (GIS) method to explore bCHP location and find population density for selected towns. The GIS is a commonly used tool for determining the availability of biomass feedstocks and minimizing transportation costs through logistics analysis and distance calculations. GIS network analysis and location-allocation analysis tools can simulate site competition for biomass resources. The research findings demonstrate that GIS, land use, resource availability, and supply chain cost data can be integrated and mapped to facilitate the determination of different sustainable factor weightings and, ultimately, to generate optimal candidate sites for biomass energy plants [41,42].

The biggest challenges confronting large-scale biomass supply are 1) the energy density. If the biomass moisture content of conventional wood is 30% in a nutshell, each ton of wood transported contains 300 kg of water. Additionally, the shape of the biomass feedstock, which includes chipped, pelletized, rounded or baled, significantly impacts bulk density and transportation economics. As a result, compaction and densification are viewed as critical components of an efficient biomass supply. 2) Apart from bulk and energy density, large-scale biomass supply is constrained by a variety of bottlenecks, including initial raw material costs, biomass producer participation, environmental regulation, and sustainability. Solving all of these issues entails establishing a future biomass commodity in Europe and throughout the world. Forest biomass energy has the advantage of being abundant, renewable, and combustible in a clean manner. However, the majority of related works focused exclusively on cost or pollution minimization, with little emphasis on the social dimension. Social enterprise develops business models to address social and environmental issues. 3) Apart from cost and carbon reduction, the aforementioned problem takes into account the objective of increasing job opportunities created by social enterprise expansion.

Additionally, the gap includes an uncertain number of inventory days, an uncertain number of job offers per unit of surplus factory scale, an undetermined amount of biomass production, and an unknown amount of biofuel demand due to fossil fuel price fluctuations. Long-term contracts for reliable feedstock supply at a reasonable price are virtually impossible to obtain. 4) Lack of sustainable profitability is also one of the reasons why many upstream firms lack driving forces for technology reform. 5) Also, one of the economic obstacles is that biomass resources are dispersed, and to minimize transportation costs, biomass projects seek to locate as close to the source as possible, resulting in biomass project centralization. Due to decentralized capital, low profitability, frequent fluctuations in international crude oil prices, and high market risk, investors rarely entered the biomass power generation industry on their own. Biomass energy generation is constrained by high capital investment and operating costs. Biomass pretreatment technologies incur additional costs that small farmers and small-scale fuel producers may not afford [43].

According to the literature review and expert opinion, several factors must be considered when determining the location of a biomass power plant, including economic, environmental, technical, and social-political factors. While numerous researchers have applied the MCDM model to various fields of science and engineering, a trend that has been increasing for many years, very few have done so in the biomass power plant location selection process. Wood residues from manufacturing, discarded wood products diverted from landfills, and non-hazardous wood debris from construction and demolition activities are the most cost-effective sources of wood fuels. Generating energy from these materials allows for the recovery of the material's energy value and avoids the environmental and financial costs associated with disposal or open burning. Throughout the country, biomass is abundant in a variety of forms. Certain types of biomass are more abundant in specific regions where the climate is more conducive to their growth. The biomass feedstocks discussed in this report are diverse in terms of their origins and fuel characteristics, and as a result, their typical considerations for utilization are also diverse [44].

Bayesian Network (BN)

A Bayesian Network (BN) concept is a model that has proven its vitality today. The Bayesian network is a model that helps us understand the relationship between different variables and how they affect different causes. A BN is a graphical model based on Bayesian theory that describes interdependencies among a set of variables via a directed acyclic graph. The prior probability of a set of variables can be updated in BNs once some new evidence is available to describe the variables. The structure of BN consists of two main concepts: nodes representing variables and arcs connecting and representing the interdependencies among a set of nodes. Nodes in BNs are classified into three levels: initial nodes that are called root or parent nodes, child or leaf nodes that depend on parent nodes, and nodes among them that are called intermediate nodes [45]. Arcs in BN represent causal relationships among variables, and to identify that, the conditional probability distribution is used based on expert and scientist knowledge.

BN is a unique method for calculating the posterior probability distribution of unknown conditional observed variables. The BN may be built up manually or automatically. For manual Bayern networks, the variables provided are known by the expert coming up with the model, but for automatic Bayern networks, the variables are generated by the software automatically. The manual Bayern networks require less research as the researcher knows the variables. However, the data may require more intense research in automated Bayern networks as the variables may be new to the researcher. The Bayesian network shows relationships between two variables, and due to its visual captivation, it is easy to identify with different probable causes of an event.

BN can handle quantitative and qualitative data types that are designed in conditional probability. The variables can be Boolean (yes/no), integer, qualitative (high/medium/low), discrete, or continuous. The ability to manipulate nodes of different types is the main characteristic of BN, which encourages us to locate and assess several alternatives to bCHP sites. Data variables can be gathered from historical data and/or expert perspectives [46].

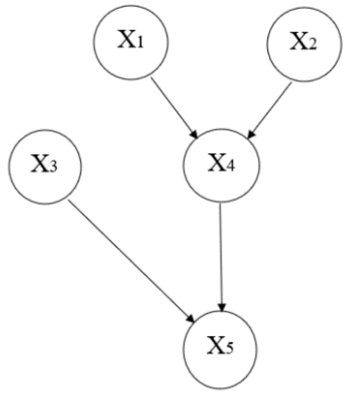


Figure 15 A Bayesian Network example with five nodes.

Figure 15 demonstrates a graphical cycle of BN example with five variables (nodes). Nodes X1, X2, and X3 are parent nodes, node X4 is an intermediate node, and node X5 is a leaf node. Equation (1) is a general full joint probability distribution of a BN consisting of n variables X1,…, Xn.

$$P(X_1, X_2, \ldots .X_n) = P(X_1|X_2, \ldots .X_n)P(X_2|X_3, \ldots .X_n) \ldots \tag{5}$$
$$P(X_{n-1}|\, X_n)\; P(X_n) = \prod_{i=1}^{n} P(X_i\, |X_{i+1}, \ldots ., X_n)$$

For the five variables shown in **Figure 15**, X_1, X_2, X_3, X_4, and X_5, equation (1) can be streamlined since we know the parents of each node. For instance, we know that X_4 has exactly two parent nodes, X_1 and X_2. Therefore, the joint probability distribution of $P(\,X_1, \ldots .X_n)$ can be substituted with $P(X_4|\,X_1, X_2)$ since only X_1 and X_2 have a significant contribution to the existence of X_4. The symmetric breakdown of the joint distribution variables is provided in equation (2).

$$P(X_1, X_2, \dots, X_5) = P(X_1)P(X_2)P(X_3)P(X_4|X_1, X_2)P(X_5|X_3, X_4) \quad (6)$$

The three unconditional probabilities in equation (2), namely $P(X_1)$, $P(X_2)$, and $P(X_3)$, and the two conditional probabilities, $P(X_4|X_1,X_2)$,and $P(X_5|X_3,X_4)$, are needed to define the joint distribution of $P(X_1,\dots,X_5)$ [47].

Another characteristic of BN is the capability to insert propagation belief P(Xi) once observing other nodes' behavior. The observed nodes are named evidence. For instance, the conditional probability for variable X5 given evidence θ, (θ = {X1, X2, X3, X4, X5}), can be used to calculate P(X5|θ) (see equation(3)).

$$P(X_5|\theta) = \frac{P(X_1,X_2,X_3,X_4,X_5)}{P(X_1,X_2,X_3,X_4)} = \frac{P(X_1,X_2,X_3,X_4,X_5)}{\sum_{X_5} P(X_1,X_2,X_3,X_4)} \quad (7)$$

This conditional probability, given in equation (3), can be calculated more efficiently by exploring conditional independencies using equation (4).

$$P(X_5|\theta) = \frac{P(X_5|X_3)P(X_4|X_1, X_2)}{\sum_{X_5} P(X_5|X_3)P(X_4|X_1, X_2)} \quad (8)$$

The Bayern network model is helpful in several ways. It is an important decision-making tool and helps analyze profit maximization in business. The Bayesian network models are used globally, especially by data scientists, to test the probable cause of an outcome and the contributing factors. Interested readers are encouraged to review [45] for details about BN modeling.

Multi-criteria Assessment for a bCHP Site Selection

Criteria assessments play a significant role in the site selection of a bCHP system. Given the key idea for this study is to reliably locate bCHP in rural communities, the siting decisions are made from the technical and sustainability perspectives. Three sub-criteria are used to define the technical requirements, namely, electrical and thermal demand, power outage frequency, and integration of renewable energy. These requirements primarily followed the basic CHP installation guidelines set forward by the U.S. Department of Energy (DOE) [48,49]. Therefore, our main focus is mainly given to the sustainability perspective, which we defined under the light of three dimensions, namely, the environmental, economic, and social criteria. Each criterion is associated with a number of sub-criteria, which are determined in multiple ways. First, an initial set of sub-criteria is identified under each criterion via reviewing academic literature and government reports (e.g., U.S. DOE, U.S. Environmental Protection Agency (EPA)), and performing an initial feasibility assessment for potential bCHP siting selection in the rural communities. Secondly, experts' opinions (e.g., stakeholders, researchers from academia, national lab, and government offices) are collected, and the initial sub-criteria list is refined. Finally, less important sub-criteria are discarded from the list, and the refined list is reviewed again with the experts. **Figure 16** delineates the criteria and sub-criteria used for evaluating bCHP site selection in a rural community. The details about the sub-criteria are provided below.

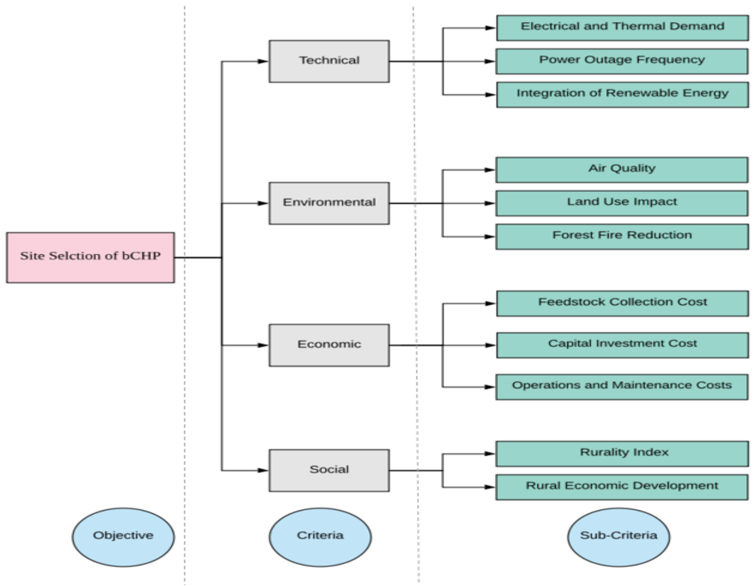


Figure 16 Criteria and sub-criteria for evaluating bCHP site selection in a rural community

Technical criterion

The following three sub-criteria are used under the technical criteria.

Electrical and thermal demand

This sub-criteria refers to the potential electrical and thermal consumption needed for the selected sites. Facilities within a rural community, such as agricultural farms, food processing facilities, paper mills, schools, hospitals, government buildings, wholesale/retailer, can be considered as a potential location to install a bCHP facility [50]. It is assumed that the candidate sites may potentially be willing to install bCHP. Further, we deduct the sites which are already using CHP facilities in our test region (obtained via [50].). The approximation of possible consumption in terms of Megawatt (MW) is considered.

Power outage frequency

This sub-criterion refers to the consistency of power supply in the potential rural areas. The reliability of a power supply is defined by how frequently the power fails or the time between failures. A power outage can be due to technical reasons (e.g., planned maintenance) and odd reasons (e.g., natural disasters). A site with a stable power supply is more desirable though preference will be given for a rural community to become operational in an isolated or disconnected mode under any extreme natural event (e.g., hurricane, tornado).

Integration of renewable energy

This sub-criteria refers to the opportunity of a rural community to utilize renewable energy sources (e.g., solar or wind) to decrease the energy production cost and increase the overall system resiliency. For instance, our test region Mississippi tends to have a short winter and a long summer, with the average temperature being 82°F during summer and 52°F during the winter [51]. Therefore, the rural Mississippi communities may benefit from integrating solar energy.

Environmental criterion

Under the environmental criteria, three main factors can play critical roles in selecting the best alternative site location for bCHP in Mississippi rural communities: air quality, land use impact, and forest fire reduction.

Air quality

Electricity generation usually impacts air quality, which results in DOE concern. Air quality standards have to adhere to the Clean air act (CAA), the DOE's primary law governor. The electric power system can generate emissions and other pollutants. However, the use of biomass for CHP can fundamentally reduce air pollution [52]. Greenhouses gases and other harmful emissions, such as carbon dioxide (CO_2) and sulfur dioxide (SO_2), will be significantly reduced using the bCHP system [46].

Land use impact

Another environmental indicator of using bCHP is to reduce the biomass residues and wood waste that occupy a large space of landfill sites. Thus, their exploitation will provide more space in landfill sites and decrease waste disposal [39].

Forest fire reduction

Wildfires have led to severe impacts on wildlife, humans, and global warming. The exploitation of the accumulated dry forest residues can reduce the risk of wildfires [39]. Using forest residues for electricity generation would be a sustainable alternative, while minimizing the risk of wildfire and possible destruction of wild habitant and the nearby local communities [53].

Economic criterion

The following three sub-criteria are used under the economic criteria.

Feedstock collection cost

The source and sustainability of the biomass feedstock significantly impact the economics behind the bCHP-based power generation. A wide range of biomass feedstocks which are abundant in the rural community, such as forest residues and wood waste, agricultural residues (e.g., corn stovers, wheat stalks), energy crops (e.g., grasses), and biogas from livestock effluent, can be considered as a potential feedstock source [39,48]. To increase the system resiliency, the bCHP site that can procure biomass feedstock from multiple sources (located within 30 miles radius from the facility), pending the conversion technology supports the feedstock types, will be weighted higher. To summarize, this sub-criteria consists of the costs associated with feedstock procurement, transportation, pretreatment, and storage costs.

Capital investment cost

Biomass can be converted into power in a wide range of commercially-proven technologies, such as the thermal-chemical processes (e.g., combustion, gasification, and pyrolysis) or biochemical processes (e.g., anaerobic digestion). Depending upon the type of processes being used, the bCHP capital investment cost varies. Note that feedstock availability and costs have a strong influence on selecting the economic biomass conversion technologies for the bCHP facilities located in a rural community.

Operations and maintenance (O&M) costs

O&M costs refer to the costs associated with safe, smooth, and reliably maintaining the day-to-day power generation operations via the bCHP systems. More specifically, O&M costs consist of labor, scheduled and unscheduled maintenance, ash disposal, insurance, equipment replacement, and many others.

Social criterion

Lastly, the following two sub-criteria are used under the social criteria.

Rurality index

Given we are assessing the potential location(s) to open bCHP facilities in a rural community, we use the Index of Relative Rurality (IRR) indicator, proposed by [53], to gauge the level of rurality a particular community belongs to. A community (e.g., county) with a higher Index of Relative Rurality (IRR) is considered more favorable for bCHP installations for this study.

Rural economic development

An assessment has been made based on the need for economic development in a rural community. Factors such as the number of existing farms and the unemployment rate are considered in this assessment [53]. Rural communities with a need for economic development are weighted higher during the bCHP site selection processes.

The Proposed Bayesian Network Methodology

This section introduces the methodology for bCHP site selection in the rural community. We broadly categorize this selection process into *three* different phases: *(i)* development phase, *(ii)* modeling phase, and *(iii)* assessment phase. The *development* phase consists of identifying several criteria and sub-criteria to locate a bCHP facility in a rural community systematically. Expert knowledge, available literature, and basic CHP installation guidelines, as mandated by the US DOE [48], are used to construct the criteria and sub-criteria. In total, four criteria and eleven sub-criteria are identified to assess a potential site for installing a bCHP unit (see **Figure 16**). Next, a proper connection between the criteria and sub-criteria is made, and the relevant data are collected to construct the BN model. With the knowledge gathered during the development phase, a BN model is constructed for each potential site during the *modeling* phase. The BN score for all potential sites will be assessed via numerous sensitivity analyses during the *assessment* phase. If validated, the analyst will select the best bCHP site(s); otherwise, the *development* phase will be visited again to reevaluate the criteria/sub-criteria selection and data collection processes. The process will continue until each site is adequately validated via rigorous sensitivity analysis.

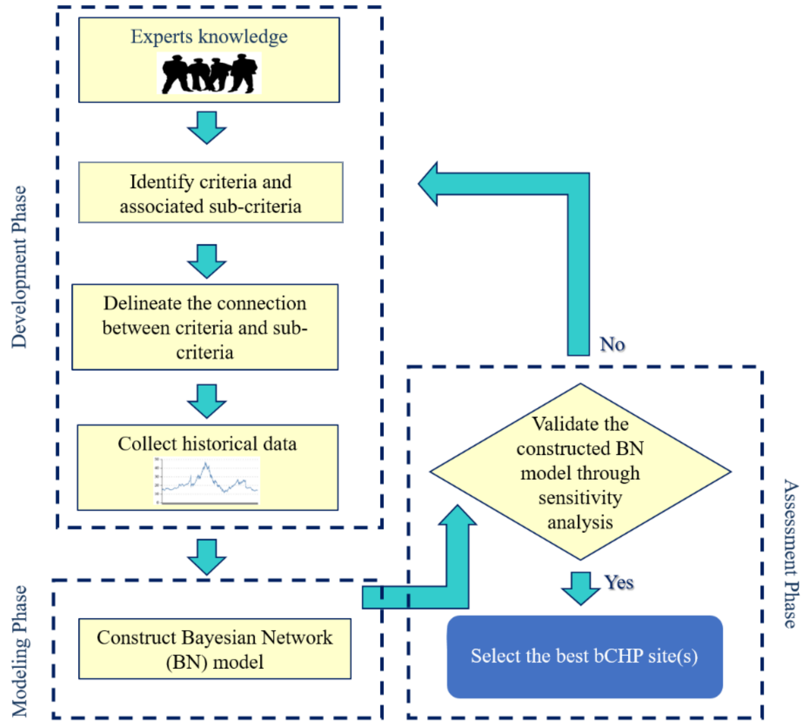


Figure 17 The designed framework for selecting a bCHP system in a rural community

Case Study

This section presents a BN model simulated using AgenaRisk software (https://www.agenarisk.com/) to evaluate possible alternatives for bCHP sites. The developed BN model is decomposed into four sub-models: technical, social, economic, and environmental. We start by assuming equal weights for all four criteria. We use the 82 counties of Mississippi as a testing ground to visualize and validate the BN model. The procedure of modeling for each sub-criteria is described below.

Modeling Criteria

This subsection discusses in detail how the four criteria are modeled, along with the data sources and assigned distributions. Below, we summarize the variables used during the modeling processes.

(i) Boolean variables are usually used to evaluate dual responses (yes, no)

(ii) Qualitative variables are usually used to assess ordinal categories utilized for weights for contributors (ranked)

(iii) Discrete variables are usually used to measure constant values

(iv) Continuous variables are usually used to evaluate random variables with an identified probability distribution; finally,

(v) The integer variables are usually used with the aspect that does not accept fractions.

Modeling of economic criterion

The economic criteria consist of three cost components: feedstock collection, capital investment, and total operations and maintenance costs. The modeling procedure for economic criterion and its contributors is summarized in **Table 6**. We use corn stover and forest residues as the primary feedstock sources for our test region due to their availability and affordability in the rural communities in Mississippi. **Figure 18** visualizes the total availability of corn stover and forest residues for the state of Mississippi. The data for the capital investment and total operations and maintenance costs are obtained from the International Renewable Energy Agency [24].

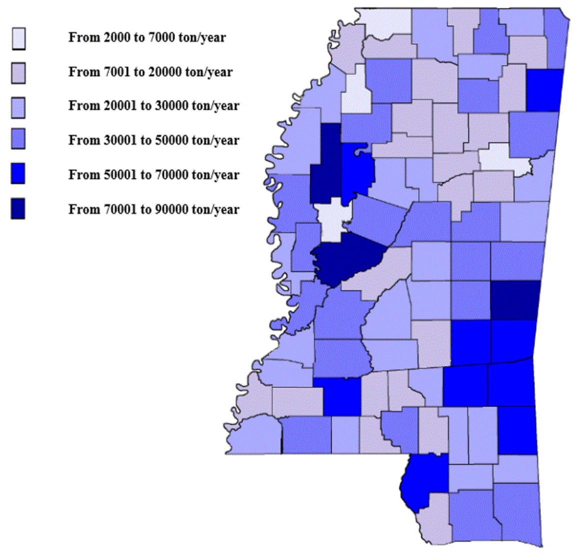


Figure 18 The availability of forest residues and corn stover for the state of Mississippi

Table 5 Modeling of variables contributed to economic criterion

Variable name	Modeling procedure	Explanation
Feedstock Collection Cost	Forest residues[1]: Triangular distribution(15, 22, 30) Corn stover[2]: Triangular distribution(20, 35, 50)	For the forest residues, we use triangular distribution with an average, minimum, and maximum feedstock collection cost of $22/ton, $15/ton, and $30/ton, respectively. For the corn stover, we use triangular distribution with an average, minimum, and maximum feedstock collection cost of $35/ton, $20/ton, and $50/ton, respectively [60].
Capital Investment Cost	TNORM(μ=18,040; σ^2=12,000; LB=1,990; UB= 28,000)	The capital investment cost is assumed to follow a truncated normal distribution with a mean of $27,930, a variance of $7,180, and a lower and upper bound of $18,000 and $37,935, respectively. Equipment (prime mover), fuel management and preparation, machinery, engineering, and construction costs are contributed to the total investment cost. The largest contribution to the capital costs of the bCHP systems is the boiler itself and the supplementary equipment, which make up approximately 60-70% of the total capital cost. An appropriate system for rural communities would be 5 MW [65, 66].
Operation and Maintenance Cost	Expected lifetime[3] x Annual Maintenance cost	The operation and maintenance (O&M) of biomass power generation plants denote the fixed and variable costs. Fixed O&M costs involve labor and routine parts exchange. On the other hand, the variable O&M costs are accompanied by the output of the biomass system. The maintenance cost is assumed to depend on the capital investment cost, with an average cost of $0.0006/MW. Annual Maintenance cost = (0.0006*Capital investment cost (CAPEX)) [61].

[1]The feedstock residues availability is assumed to follow a truncated normal distribution with an average mean of 31,366 ton and a variance of 18,022 ton, with lower and upper bound of 2,957 ton and 89,760 ton, respectively.
[2]The corn stover availability is assumed to follow a truncated normal distribution with an average mean of 5,887 ton and a variance of 15,163 ton. The lower bound is zero since many counties in Mississippi do not produce corn stover, while the upper bound is 81,966 ton.
[3]The expected lifetime of the bCHP system is assumed to follow a triangular distribution with a lower, average, and an upper lifetime of 15 years, 20 years, and 25 years, respectively [60].

Modeling of technical criterion

The technical criterion compromises the reliability of a facility's power supply and the potential electrical and thermal consumption needed near the site locations. Therefore, the site location's reliability that supplies power is measured based on the average failure of a certain community’s power outage. Moreover, a community with more available businesses, houses, hospitals, and schools in the rural community is recommended. Since we are investigating the potential of siting a bCHP facility in a rural community, we restrict the power plant capacity to 5 MW [30]. **Table 7** shows how the variables are modeled under the technical criteria to locate a bCHP facility in a rural community.

Table 6 Modeling of variables contributed to the technical criteria

Variable name	Modeling procedure	Explanation
Electrical and Thermal demand	IF(Housing Occupancy[1] >= 3,000 & Business Occupancy[2] > 12.0, "True","False")	To model the needed electrical and thermal demand, it is necessary to identify the minimum power and heat threshold required to define the right system capacity in a rural community. The 5 MW per day power system can be considered satisfactory for a rural community with a minimum housing and business occupancy of 3,000 and 12, respectively [65,66].
Power Outage Frequency	NORM(μ=90, σ^2=75) IF(Power outage < 110, "True","False")	The power outage can be considered a critical factor to ensure a system’s overall reliability. The average power outage in Mississippi is reported to be 110, with a variance of 75 [51].
Integration of Renewable Energy (e.g., solar system)	IF(Renewable energy: solar = 1.0,"True","False")	Solar energy is considered to increase the system's resiliency. As per the Biofuels Atlas, seven counties located in the central and the northeast region of Mississippi are suitable for solar energy [51]. We select one if the county is suitable for solar energy integration; zero otherwise.

[1]The housing occupancy rate is assumed to follow a truncated normal distribution with an average, variance, lower, and upper bound to be 3,000, 1,090, 2,500, and 8,000 residential areas, respectively; i.e., TNORM (μ = 3,000, σ^2 = 1,090, LB= 2,500,UB= 8,000)) [63].
[2]The business occupancy rate is assumed to follow a truncated normal distribution with an average of 16 (includes retailer, plant, warehouse, store, and station), variance 3, lower and upper bound to be 12 and 40 businesses, respectively; i.e., TNORM (μ = 16, σ^2 = 3, LB= 12, UB= 40) [58].

Modeling of environmental criterion

The environmental criterion consists of three variables: air quality, land use impact, and forest fire reduction. A Boolean variable with a true or false state is used to model the environmental node. The true state indicates a positive outcome, while the false state indicates a negative result. **Table 8** shows how the variables are modeled under the environmental criteria to locate a bCHP facility in a rural community.

Table 7 Modeling of variables contributed to environmental criteria

Variable name	Modeling procedure	Explanation
Air Quality[1,2]	IF(CO_2 <= 150 & SO_2 <=7,040,"True","False")	The if condition is used to define the threshold levels for CO_2 and SO_2. To model the air quality level for a given rural community, the quality index thresholds are set to be 150 and 7,040, respectively [55,56].
Land Use impact	IF(Forest logging residues[3] >21,955 or corn stover[4] >3,944,"True","False")	For modeling the land use impact, the if condition is used to determine the minimum usage of forest residues or corn stover to be utilized by a particular site in an attempt to reduce waste in the regions [57,58].
Forest Fire Reduction	IF(Forest wildfire[5] >7 or Total disaster occurrence[6] >10,"True","False")	If a location (e.g., county) is impacted more frequently by a forest fire or other natural catastrophes (e.g., hurricanes and tornados), we assume that there would be a higher inclination to locate a bCHP facility in that location. Based on the historical data in Mississippi, counties with higher than 7 forest fires or 10 natural catastrophes are considered favorable for siting a bCHP facility [59,60].

[1]The CO_2 level (ppm) is assumed to follow a truncated normal distribution with an average of 150 ppm, a variance of 15 ppm with a lower and upper bound of 100 ppm and 168 ppm, respectively; i.e., TNORM (μ = 150, σ^2 = 15, LB= 100, UB= 168) [55].

[2]The level of SO_2 (ppb) is assumed to follow a truncated normal distribution with an average 7,040, variances of 2,835 with a lower and upper bound of 3,900 and 12,200 ppb, respectively; i.e., TNORM (μ = 7,040, σ^2 = 2,835, LB= 3,900, UB= 12,200) [56].

[3]Availability of logging forest residue is assumed to follow a normal distribution with a mean of 21,955 tons and a variance of 12,615 tons; i.e., NORM (μ = 21,955, σ^2 = 12,615) [57].

[4]Availability of corn stover is assumed to follow a normal distribution with a mean of 3,944 tons and a variance of 1,015 tons; i.e., NORM (μ = 3,944, σ^2 = 1,015) [58].

[5]The wildfires in Mississippi are assumed to follow a truncated normal distribution with a mean of 7 wildfires, a variance of 5 wildfires, and a lower and upper bound are 1 and 28 wildfires, respectively. **Figure 19** shows the data collected from the Mississippi Forestry Commission (MFC); i.e., TNORM (μ=7, σ^2=5, LB= 1, UB= 28) [59].

[6]The number of disasters (e.g., hurricanes, tornados) in Mississippi is assumed to follow a normal distribution with an average and variance of 10 and 6, respectively. **Figure 20** shows the data collected from the Mississippi State Fire Incident department (MSFI); i.e., NORM (μ=10, σ^2=6) [60].

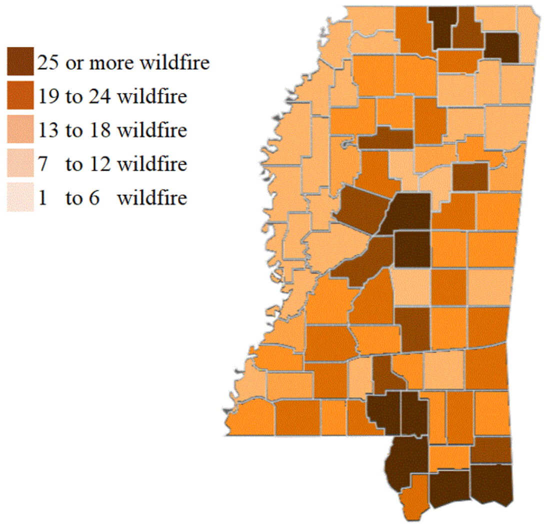


Figure 19 The average number of wildfire per county from 1/2016 to 12/2020 [59]

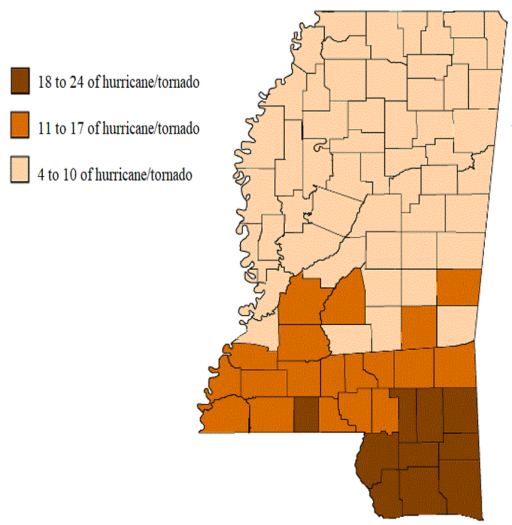


Figure 20 The number of disaster occurrence per county from 1/2015 to 12/2020 [60]

Modeling of Social criterion

The social criterion consists of two variables: (i) rurality index and (ii) rural economic development. The relative rurality index measures the rurality in two aspects, namely, the *discrete* and *continuous* measures. Given that this study aims to investigate the bCHP site selection decisions in the rural community, the following discrete measures are used to serve this purpose: population size, population density, and remoteness from urbanized areas. On the other hand, the continuous measure captures the community health, knowledge, and standard of living typologies. The second sub-criteria in rural economic development contributes to social service in rural communities. Factors such as the number of existing farms and the unemployment rate are considered in this assessment [53]. **Table 9** shows how the variables are modeled under the social criteria to locate a bCHP facility in a rural community.

Table 8 Modeling of variables contributed to social criterion

Variable name	Modeling procedure	Explanation
Rurality Index	IF (Population size[1] < 20,000.0 or Index of relative rurality[2] > 0.59,"True","False")	To identify the rural community, a population with a size less than 20,000 is considered. Additionally, the Index of Relative Rurality (IRR) is set to be greater than 0.59 based on the studies from [53] and [54], where an IRR value of 0 implies most urban, and 1 implies most rural communities (see **Figure 21**).
Rural economic development	IF(Unemployment rate[3] > 5.9 & Business Occupancy[4] >12,"True","False")	To model rural economic development, counties with an unemployment rate of more than 5.9% (see **Figure 22**) and business occupancy with more than 12 different businesses are considered [64, 65].

[1]Population size follows a truncated normal distribution with an average, variance, lower, and upper bound to be 36,448, 30,000, 1,328 and 241,774 residents, respectively, i.e., TNORM (μ=36,448, σ^2=30,000, LB=1,328, UB=241,774) [28].
[2]The relative rurality index follows a truncated normal distribution with an average, variance, lower, and upper bound to be 0.55, 0.167, 0.01, and 0.89; i.e., TNORM (μ=0.55, σ^2=0.167, LB= 0.01, UB= 0.89) [17].
[3]The unemployment rate in Mississippi follows a truncated normal distribution with an average of 5.9%, a variance of 1.2%, and a minimum and maximum unemployment rate of 3.7% and 14.1% across all counties; i.e., TNORM (μ=5.9, σ^2=1.2, LB= 3.7, UB= 14.1) [29].
[4]The business occupancy rate follows a truncated normal distribution with an average of 12 different types of business, and a variance, lower, and upper bound to be 3, 12, and 40, respectively; i.e., TNORM (μ=16, σ^2=3, LB= 12, UB= 40) [28].

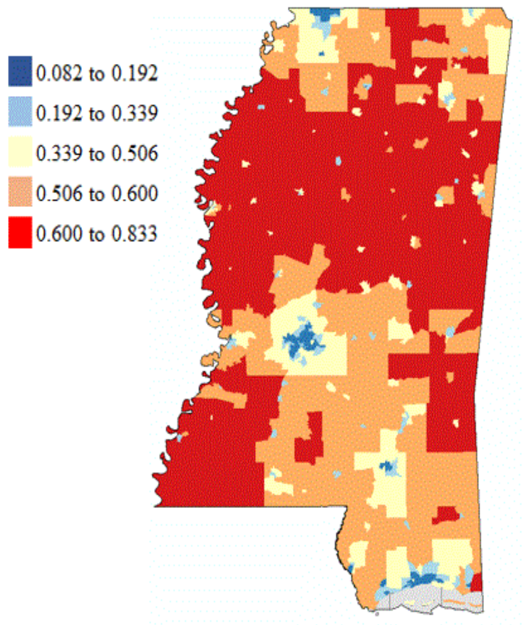


Figure 21 Degree of Rurality at Census tract-level [53]

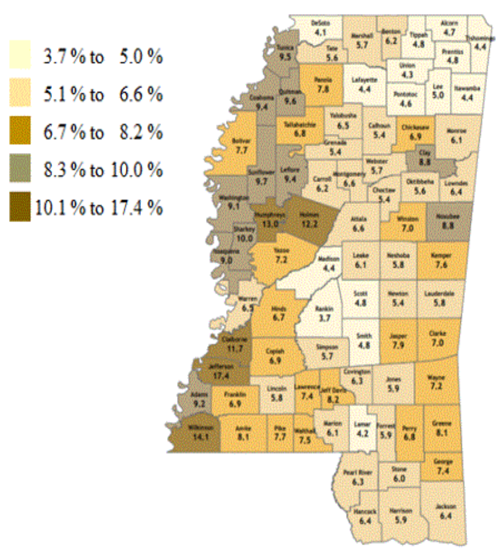


Figure 22 County-wise unemployment (in percentage) in Mississippi [65]

Experimental Results

Probability of site selection

The probability of bCHP site selection node (see **Figure 23**) is the target node in the BN model. The desired node is conditioned based on four previously mentioned criteria, namely, technical, environmental, technical, and social, which contribute to the probability of selecting a bCHP facility in a geographical region. More specifically, the probability of a given site is calculated based on the following formula: $Pr(\text{site selection}) = Pr(\text{environmental criteria being true}) \times weight_{environmental} + Pr(\text{economic criteria being true}) \times weight_{economic} + Pr(\text{technical criteria being true}) \times weight_{technical} + Pr(\text{social criteria being true}) \times weight_{social}$. In the above formula, Pr represents the probability and $weight_{environmental}$, $weight_{economic}$, $weight_{technical}$, and $weight_{social}$ to represent the weight of environmental, economic, technical, and social criteria, respectively. For our base case experiments, we set $weight_{environmental}$, $weight_{economic}$, $weight_{technical}$, and $weight_{social}$ to be 20%, 30%, 30%, and 20%, respectively.

Table 11 shows the ranking of the top ten potential favorable locations to site a bCHP facility in the Mississippi State. **Figure 27** visualizes the geographical locations of the top ten favorable bCHP site alternatives. Based on **Table 11**, it can be observed that Bolivar County is selected to be the most favorable location to site a bCHP facility in Mississippi, followed by Clarke and Coahoma Counties. Based on the BN model, the site selection probabilities for the three counties are 91.9%, 87.7%, and 81.3%, respectively. Both the three counties are rich in biomass resources (see **Figure 18**) and have a high rurality index (see **Figure 21**), making them favorable to site a bCHP facility in Mississippi. **Figure 24, 25,** and **26** show the BN network for the Bolivar, Clarke, and Coahoma Counties.

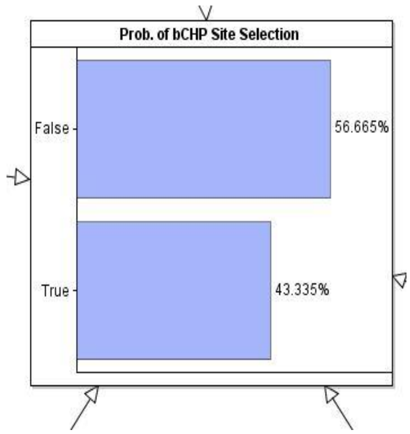


Figure 23 The BN model's target node – Probability of bCHP site selection

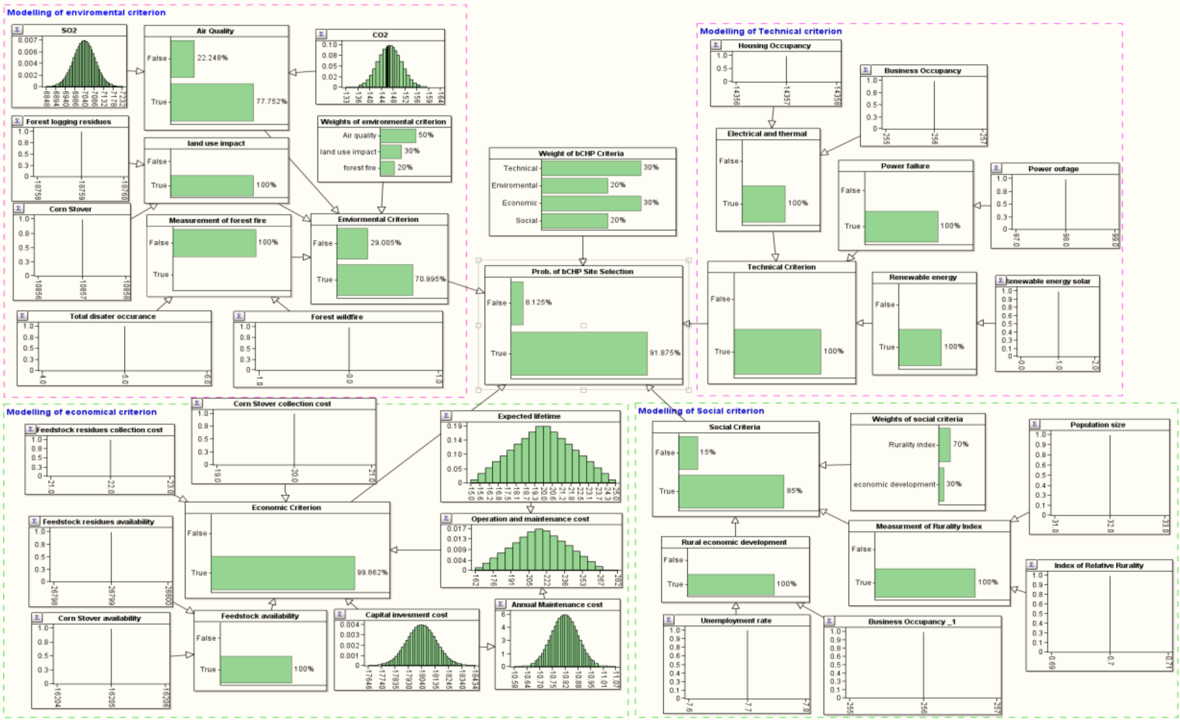


Figure 24 The developed BN model for the first bCHP alternatives in Bolivar County

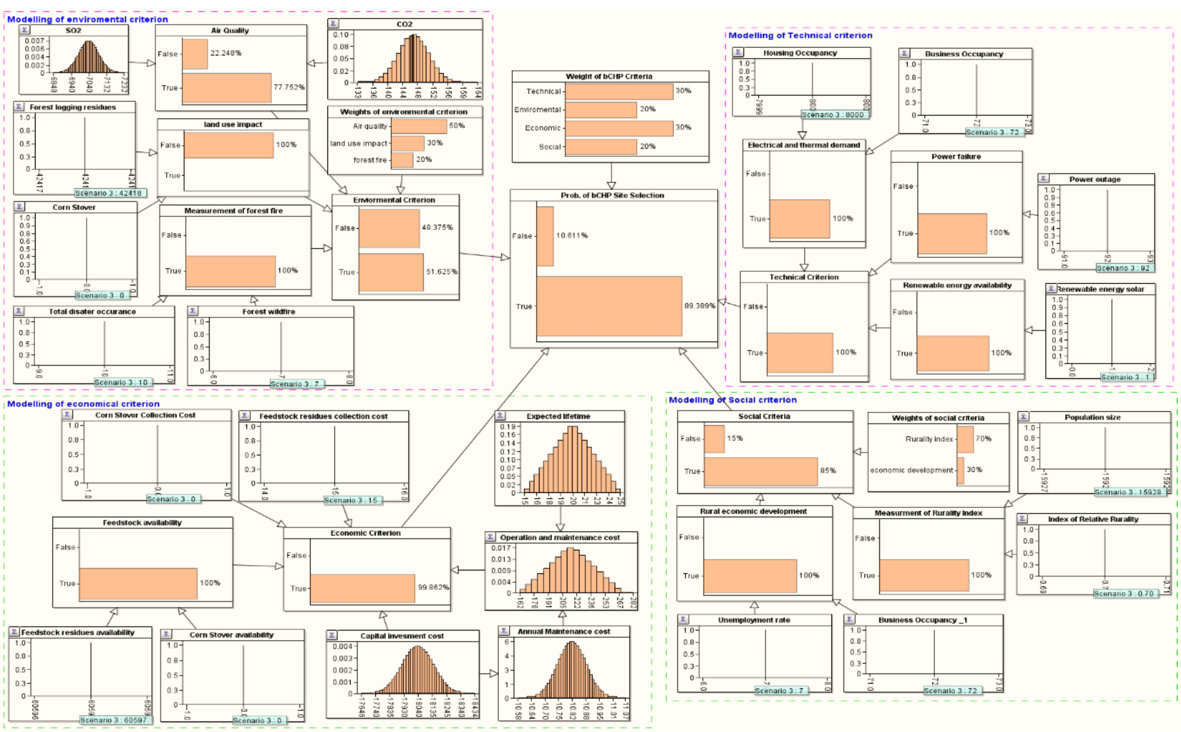


Figure 25 The developed BN model for the first bCHP alternatives in Clarke County

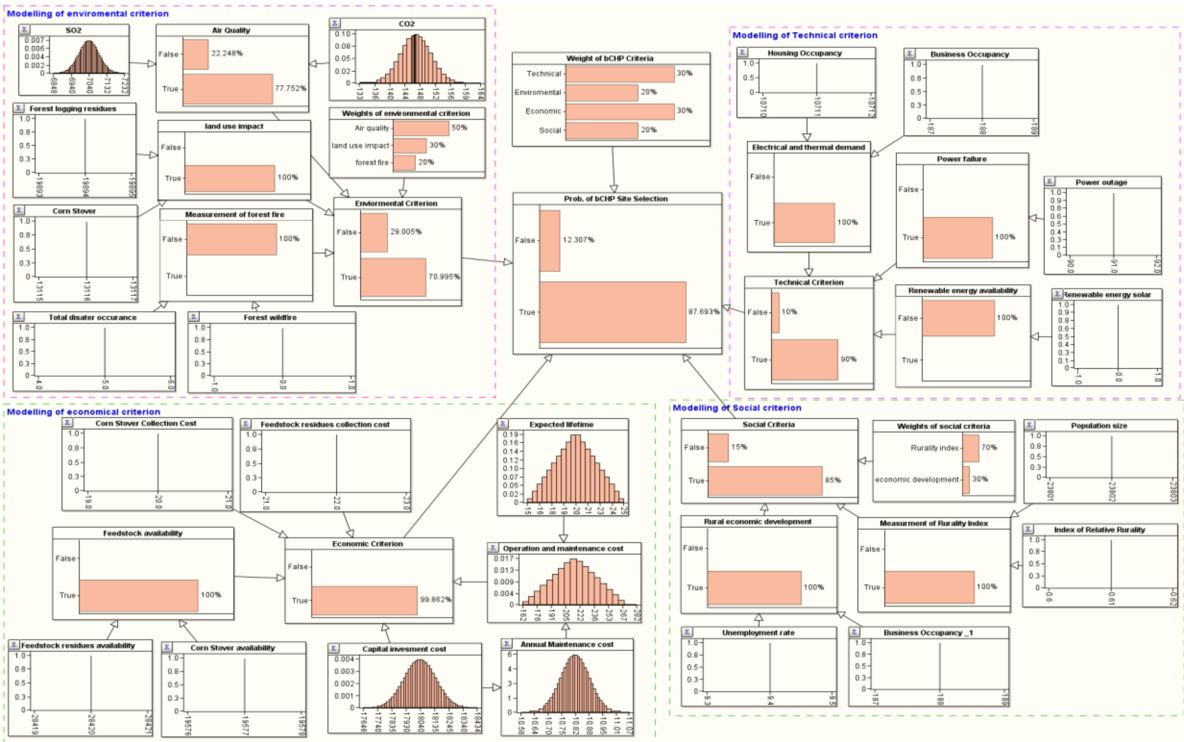


Figure 26 The developed BN model for the first bCHP alternatives in Cohama County

Table 9 Ranking of top 10 bCHP locations in Mississippi State (see **Figure 27**)

Ranking	County Name	Site Selection Probability (%)		Region
		True	False	
1	Bolivar	91.9 %	8.1%	Delta region
2	Clarke	89.4%	10.6%	Coastal Region
3	Coahoma	87.7%	12.3%	Delta region
4	Monroe	81.3%	18.7%	Northeast region
5	Leflore	80.1%	19.9%	Delta region
6	Itawamba	77.3%	22.7%	Northeast region
7	Pearl River	77.2%	22.8%	Coastal region
8	Warren	77.1%	22.9%	Central region
9	Lincoln	76.3%	23.7%	Central region
10	Greene	76.2%	23.8%	Coastal region

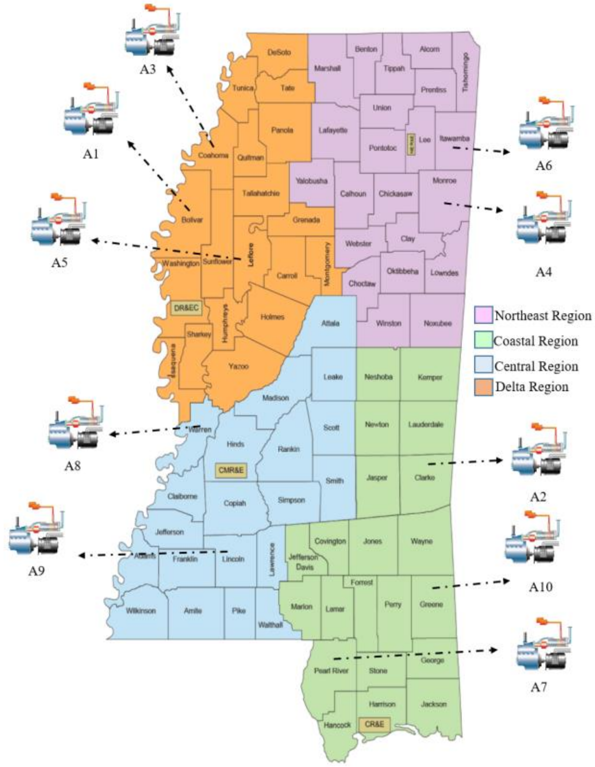


Figure 27 The geographical locations of the top 10 bCHP site alternatives.

Sensitivity analysis

Sensitivity analysis is a technique used to assess the validity of the built model. Also, to understand which nodes have more influence on the target node. This process will show how accurate the method is on the built model. It will help the system's model to see if it is within acceptable tolerance or not. We applied validation to compare the results of a model to the physical measurements, then computed a confidence interval of the difference. This formulation can also provide estimates for the system's behavior when no data are available. Therefore, a sensitivity analysis was made on the target node (probability of bCHP selection on the four criteria (environmental, economic, social, and technical).

The outcomes of sensitivity analysis on the probability of selecting counties are explained in the Tornado graph in **Figures 28 and 29**. The Tornado graphs have been utilized for sensitivity analysis purposes by comparing the significance of nodes. The variables are embodied by bars with two states of “true” and “false.” From a purely visual perspective, the length of the bars in the tornado graph measures the influence of that variable on the probability of county selection of site location. Thus, the tornado graph’s technical criterion and environmental criterion show the most significant and least significant influence on the county’s selection of the first site alternative. The general understanding is that the probability of selecting the first county location (“true”) that is based on technical criterion goes from 0.16 (when the technical criterion is “false”) to 0.55 (when a technical criterion is “true”). To be more precise, the probability of selecting the first county’s location is 0.55, given the technical criteria are achieved. This range (0.16–0.55) is precisely the bar in the tornado graph explained in **Figure 28**.

On the other hand, for the environmental criteria, the range differs from (0.42 to 0.44), indicating the low influence of the environmental criterion on the selection of site location’s decision process. The vertical bar on the chart mainly represents the marginal probability for the first alternative county location being “true” (0.44). As shown in **Figures 28 and 29**, it can be determined that the probability of selecting the first alternative site location is more sensitive to the changes in the states of technical criterion and least sensitive to changes in environmental criterion. This can also be understood that technical criterion subsidizes the most to the variability of the site location variable. Consequently, decision-makers have to concentrate more on the technical criteria than other variables.

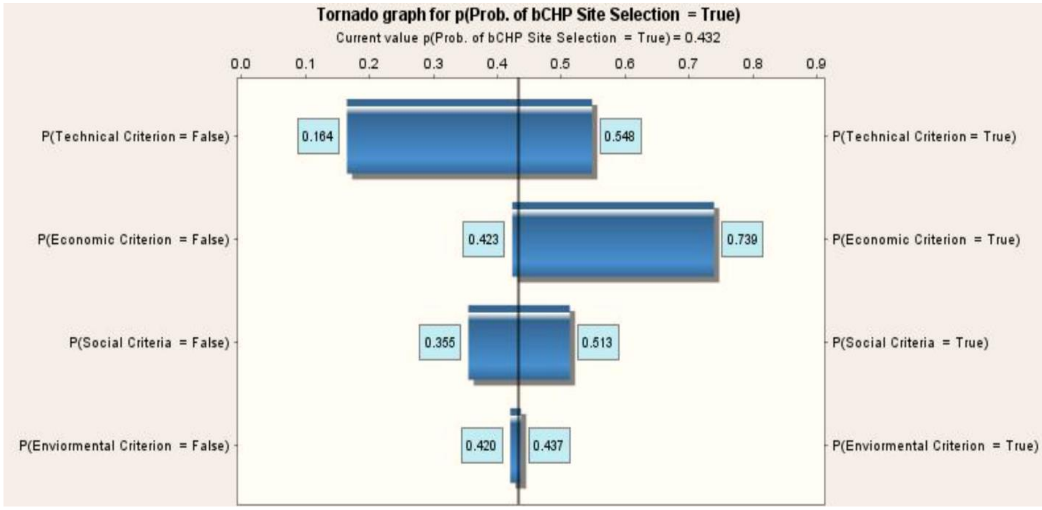


Figure 28 The tornado diagram express the effect on the first site alternative being "True".

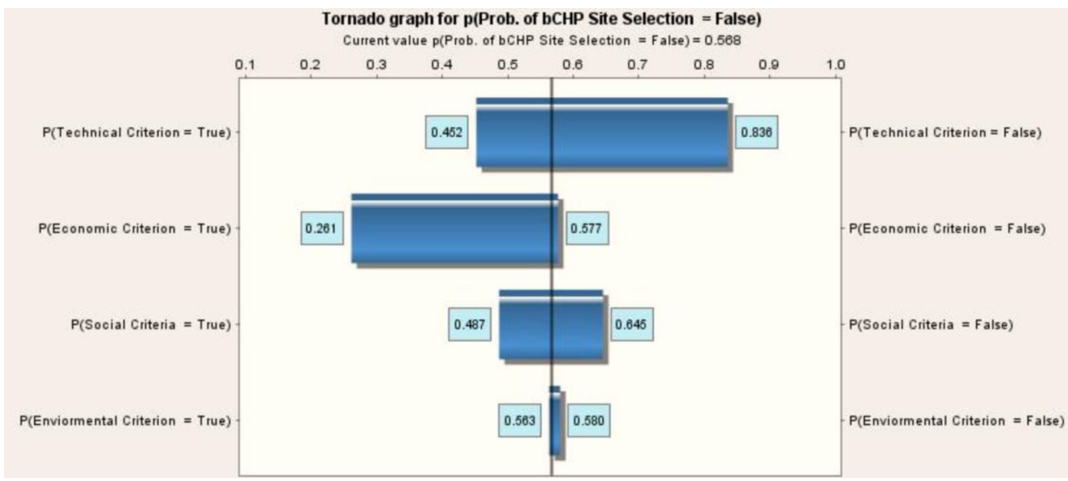


Figure 29 The tornado diagram expresses the effect on the first site alternative being "False".

In the next set of experiments, we vary the base weighs (i.e., ($weight_{environmental}$, $weight_{economic}$, $weight_{technical}$, $weight_{social}$) = (20, 30, 30, 20)%) to examine how the weights on different criterion impact the bCHP site selection decisions. To carry out the experiments, we create three different scenarios. **Table 12** shows the weight set for the three scenarios. In the first scenario, it is assumed that the economic criterion is significantly more important compared to the other criteria. As such, the weight for this scenario is set as follows: ($weight_{environmental}$, $weight_{economic}$, $weight_{technical}$, $weight_{social}$) = (10, 70, 10, 10)%. Likewise, scenarios 2 and 3 are constructed assuming that the technical and social criteria are more important as compared to the other criteria. Note that the environment criterion is neglected in the sensitivity analyses since the criterion has minimal impact on our study region.

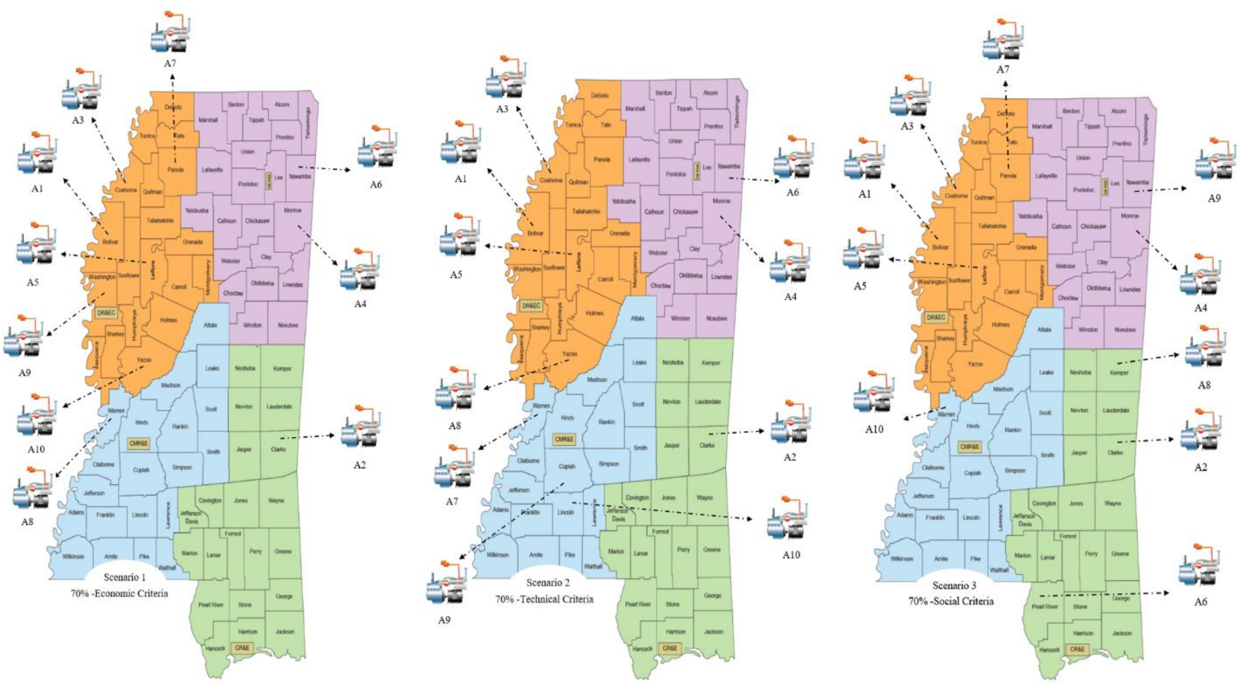
Table 10 Weight set for different scenarios

Scenario	**Weights**
1	($weight_{environmental}$, $weight_{economic}$, $weight_{technical}$, $weight_{social}$) = (10, 70, 10, 10)%
2	($weight_{environmental}$, $weight_{economic}$, $weight_{technical}$, $weight_{social}$) = (10, 10, 70, 10)%
3	($weight_{environmental}$, $weight_{economic}$, $weight_{technical}$, $weight_{social}$) = (10, 10, 10, 70)%

The bCHP sites selected under the three scenarios described in **Table 12** are listed in **Table 13** and visualized in **Figure 30**. Results in **Table 13** indicate that the top five counties in Mississippi, namely Bolivar, Clarke, Coahoma, Monroe, and Leflore Counties, are robust for locating a bCHP facility, despite higher weights being put on the economic, technical, and social criteria. However, we observe a change in the rankings of bCHP sites under all three scenarios after the top five preferences. For instance, scenario 3 diversifies the selection of bCHP facilities compared to the base case by putting more weightage on counties with a higher rurality index and economic development opportunities. A comprehensive BN network modeling for the Boliver county under scenarios 1 to 3 is visualized in Appendix **A2**.

Table 11 Top ten bCHP sites under different scenarios as discussed in **Table 12**

Ranking	Scenario 1		Scenario 2		Scenario 3	
	County Name	**Site Selection Probability (%)**	**County Name**	**Site Selection Probability (%)**	**County Name**	**Site Selection Probability (%)**
1	Bolivar	93.9%	Bolivar	93.9%	Bolivar	90.6%
2	Clarke	92.8%	Clarke	92.7%	Clarke	87.3%
3	Coahoma	89.5%	Coahoma	89.4%	Coahoma	87.3%
4	Monroe	87.1%	Monroe	87.1%	Monroe	86.3%
5	Leflore	86.4%	Leflore	86.4%	Leflore	83.4%
6	Itawamba	82.0%	Itawamba	79.6%	Pearl River	83.4%
7	Panola	79.6%	Warren	79.6%	Panola	83.4%
8	Warren	79.6%	Yazoo	79.6%	Kemper	83.4%
9	Washington	79.6%	Copiah	78.8%	Itawamba	83.4%
10	Yazoo	79.6%	Lincoln	78.8%	Warren	83.3%



(a) **(b)** **(c)**

Figure 30 Visualizing bCHP sites under (a) scenario 1, (b) scenario 2, and (c) scenario 3

Conclusion

This study is the first to methodologically investigate bCHP site selection decisions in a rural community. The site selection decision of a candidate bCHP facility is made under four dimensions: technical, economical, environmental, and social. A number of sub-criteria are developed under each criterion to methodologically assess a candidate bCHP site. All the criteria and sub-criteria are added under a Bayesian Network (BN) framework to assess the likelihood of opening a bCHP facility. Overall, 82 counties in Mississippi are assessed and visualized under different scenarios. We observe that the top five favorable locations to locate bCHP facilities in Mississippi are Bolivar, Clarke, Coahoma, Monroe, and Leflore County. These counties are rich in biomass resources, marked as rural counties, and frequently impacted by power outages. Further, it is observed that these counties are insensitive to changing technical, economic, and social metrics, indicating the counties are reliable for locating a bCHP facility. Due to our application area, we observe little to no impact of environmental criteria in locating a bCHP facility in this study.

This study can be extended in several research directions. Even though the criteria and sub-criteria utilized in constructing the BN model developed in this study are generic, it might be interesting to examine how the model behaves in selecting bCHP facilities under varying and harsh climatic conditions (e.g., Alaska). Further, the developed BN model could be integrated with different advanced machine learning models to improve the prediction quality of selecting a bCHP facility in a targeted community. These issues could be addressed in future studies.

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APPENDIX A

CHAPTER I IN STREAM MARINE LITTER COLLECTION STANDARD MODEL USING BAYESIAN NETWORK

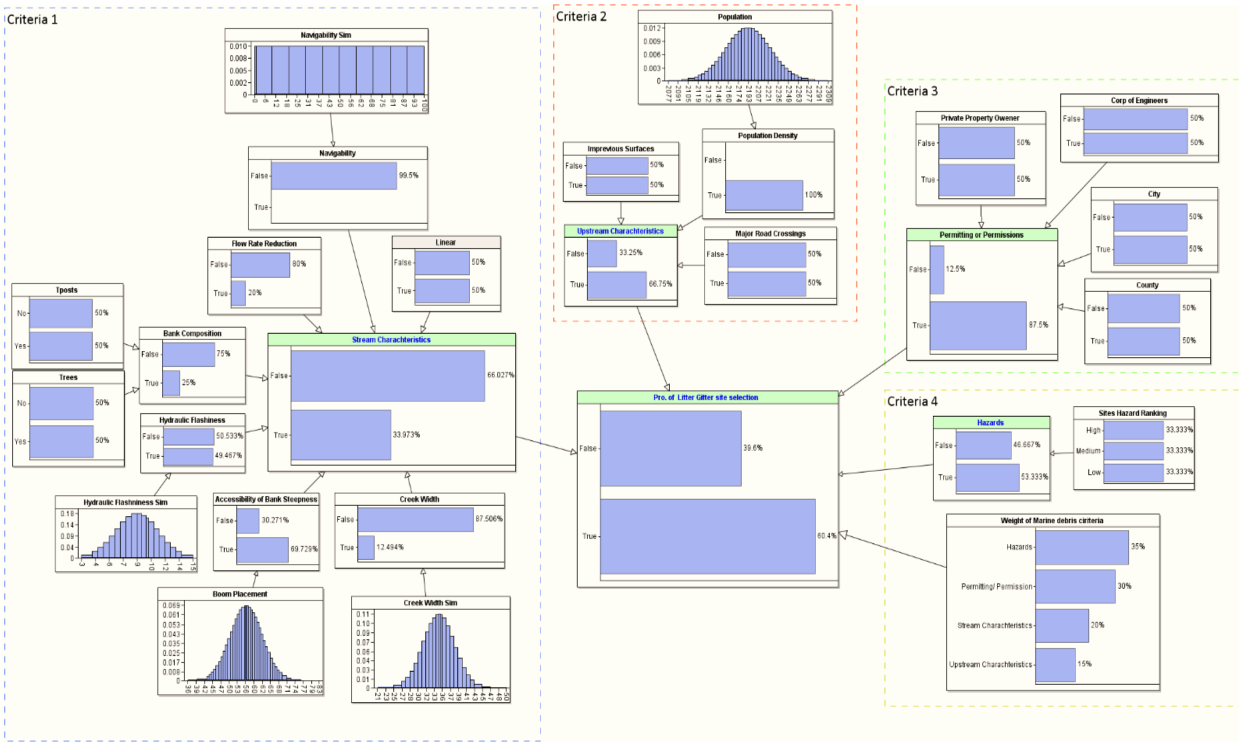

Figure 31 The developed BN model standard for LG selections.

APPENDIX B

CHAPTER II BOLIVAR COUNTY BAYESIAN NETWORK MODEL FOR SCENARIO 1,2 AND 3

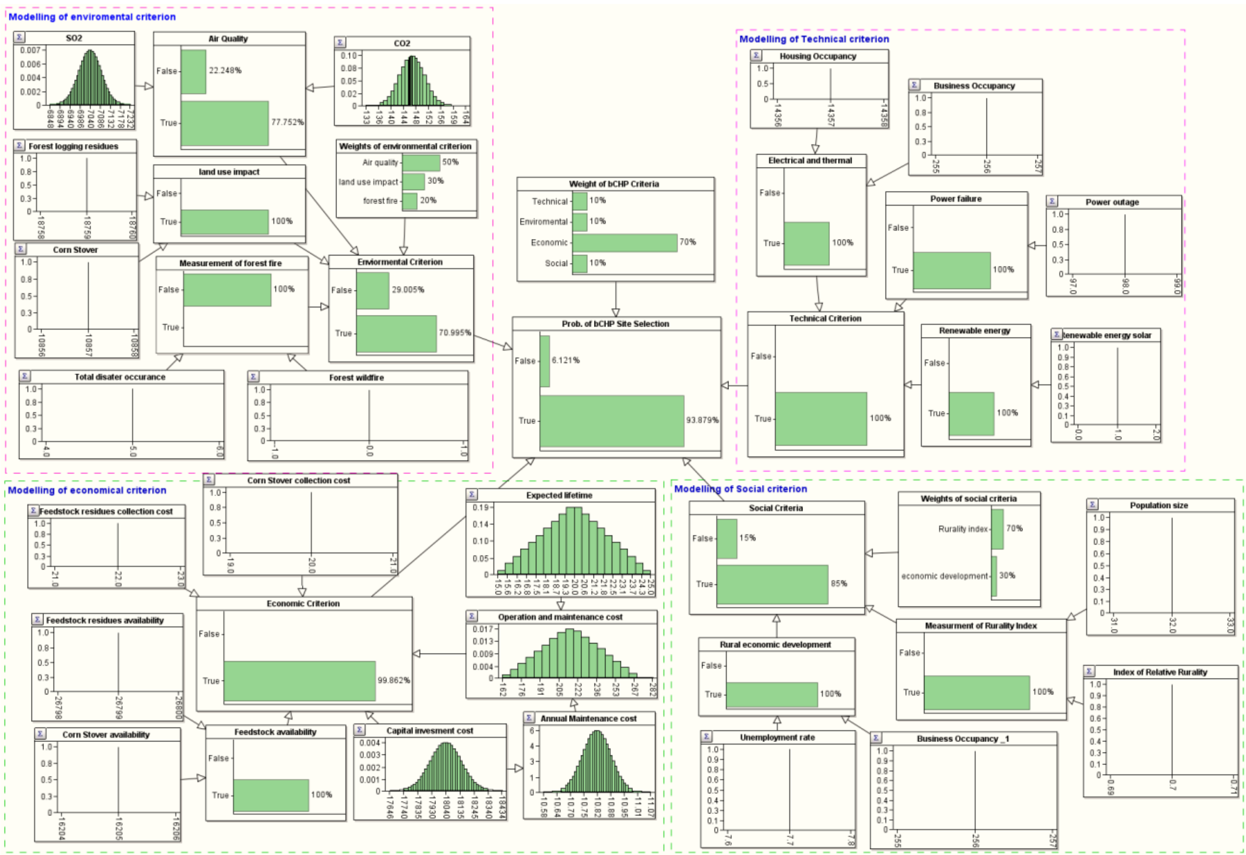

Figure 32 The developed BN model for the Bolivar County under scenario 1

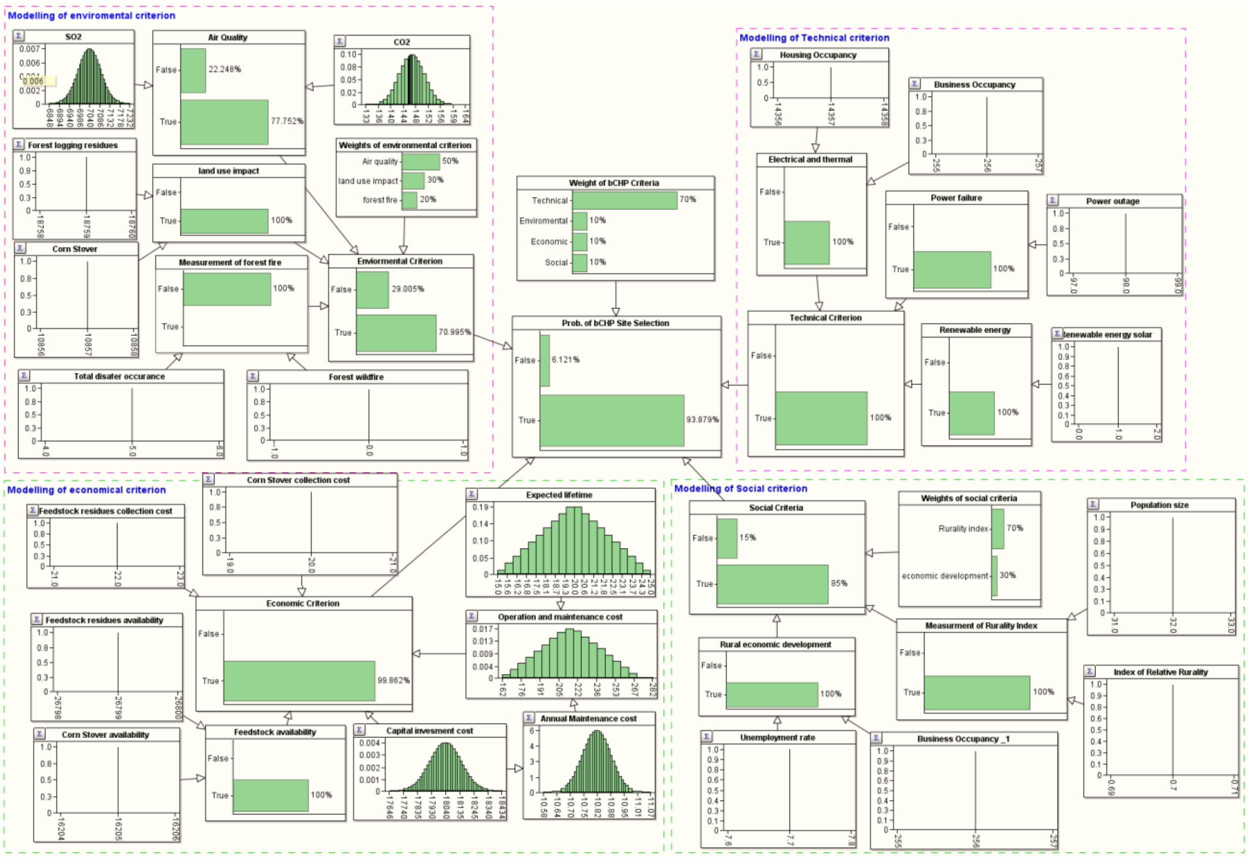

Figure 33 The developed BN model for the Bolivar County under scenario 2

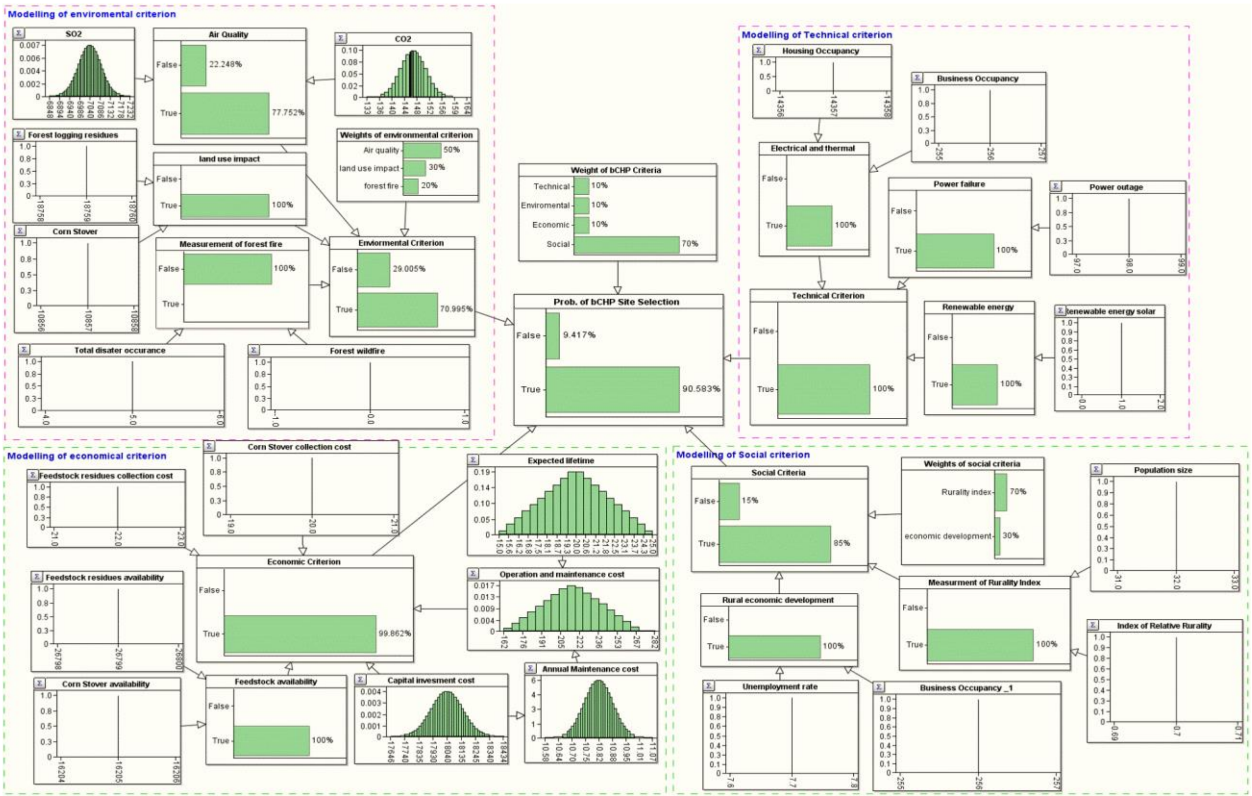

Figure 34 The developed BN model for the Bolivar County under scenario 3