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Development of a Bayesian network model for assessing the resilience of biomass-based combined heat and power system

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Due to the growing number of diverse power systems disruptions, including extreme weather events, technical factors, and human factors, assessing and quantifying the resilience of electric power subsystems has become an indispensable step to develop an efficient strategic plan to enhance the resilience and reliability of these systems and to endure the diverse interruptions. In this study, factors and sub-factors that may have either direct or indirect impact on the resilience of biomass-based combined heat and power systems are identified, and the interdependencies among them are determined as well. A Bayesian network model is implemented to quantify the resilience of a bCHP system, and the results are analyzed by applying three different techniques, which are sensitivity analysis, forward propagation analysis, and backward propagation analysis.

DEDICATION

I would like to dedicate this thesis to my parent, siblings, and friends for their support.

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I would like to thank the Saudi Arabian government for the financial support, and I also would like to thank Dr. Mohammad Marufuzzaman, my major advisor and committee chairman, for the guidance and support. I also would like to thank my committee members Dr. Junfeng Ma and Dr. Linkan Bian for assessing the completion of this thesis.

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CHAPTER I

INTRODUCTION

The industry of electric power is considered as the cornerstone of the economic sectors in the United States. Many economic sectors extremely depend on the electric power industry in order to utilize the generated electric power to perform their work in the global market. Some of these economic sectors are considered as critical infrastructures that depend completely on the electricity grid, such as emergency services, telecommunication sectors, and transportations; consequently, power disruptions may lead to affect the critical infrastructures (U.S. Department of Energy, 2015).

There are many factors that cause power disruptions across around 3 thousand electric power distribution systems in the United States, such as extreme weather events. In 2018, the average duration of the power outage in the U.S. was almost 6 hours per customer (EIA, 2020). In addition, the electric power systems infrastructures in the U.S. are aging, and they are at the end of their lifespans or near it (Johansen & Tien, 2017). Moreover, electric power systems infrastructure in the U.S. even vulnerable to various threats, including natural disasters. Power disruptions in the U.S. have a great impact on the public's security and health, and they cost from \$18 to \$70 billion annually (Hossain et al., 2019).

The electric power demand in the U.S. is increasing rapidly, and it is expected that the electricity demand will increase from 3826 billion kWh in 2012 to 4954 billion kWh in 2040. Therefore, in order to cope with the expected increase in electricity demand efficiently, essential improvements and enhancements are required to increase the power systems reliability and efficiency, and one of the alternatives that could improve the power system efficiency are microgrid systems that have the ability to operate in different operational modes, such as standby, parallel, and island mode (Marino et al., 2018).

Combined heat and power, CHP, is an electric power generation plant that dually produced electric power and thermal energy, and it has been broadly utilized in microgrids systems (Haghifam & Manbachi, 2011; Naderipour et al., 2020; Balli et al., 2007). Thus, instead of wasting heat resulting from the electricity production, CHP systems capture and use it (Chittum & Relf, 2019). CHP systems have been utilized worldwide as the major alternative electricity power system to traditional systems, and they are considered as renewable energy that saves energy and conserves the environment as well (Dong et al., 2009). CHP systems are also considered as a successful, efficient, and underutilized short-term energy solution to help the U.S. improve the reliability of the energy systems and infrastructures as well as improve the quality of the environment (EPA, 2012). Moreover, the U.S. government have started in the recent years promoting CHP systems by proposing various incentive and inducement policies to encourage the usage of CHP Systems (Zhang et al., 2016).

In 2003, large parts of the Midwest and the Northeast regions in the United States suffered from an electric power blackout. About 50 million people across six states were affected, and about 61,800 MW of the electric power load was down. Many businesses and manufacturers had huge economic losses due to the power blackout. The total economic cost in the U.S. is estimated between $4 and $10 billion. However, during the blackout, various facilities had backup generators resources, such as combined heat and power systems, CHP, and that enabled them to remain operations (Carlson & Hedman, 2004). CHP systems also have proven their high reliability by empowering different critical facilities to remain their operations during various major hurricanes that caused power outages, such as Hurricanes Harvey, Irma, and Maria in 2017, and Hurricane Sandy in 2012 (DOE, 2019). In other words, CHP systems contributed to increasing the resilience of power in these facilities in the middle of the many blackouts.

Besides the reliability and resiliency, CHP systems have many various benefits, including economic, environmental, efficiency benefits. It helps decrease energy costs, reduce harmful emissions, and increase power efficiency. **Figure 1.1** illustrates the efficiency difference between CHP and conventional station power generation. In order to produce 30 units of electricity and 45 units of steam, the conventional station power generation consumes 147 units of fuel, resulting in an overall efficiency of 51%. However, to produce the same amount of electricity and thermal units by a CHP system, the CHP requires 100 units of fuel, resulting in an overall efficiency of 75% (EPA, 2017).

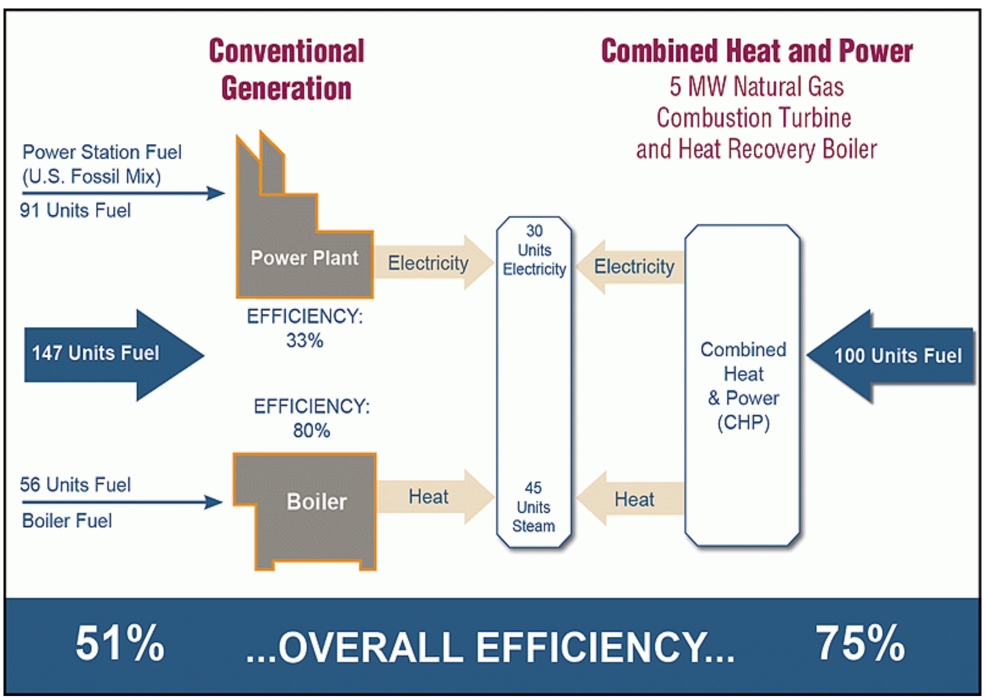

Figure 1.1 An efficiency comparison between conventual generation and CHP (EPA, 2017).

In this thesis, our purpose is to quantify the resilience and reliability of biomass-based combined heat and power systems in order to make a decision of integrating it with an existed power system as a standby or parallel generator by developing a Bayesian network model via a powerful software called Aginarisk. Plant Watson in Southern Mississippi is used in this research paper as a case study to demonstrate the quantification of the resilience of the bCHP. The fuel of the CHP system is biomass pellet, which is one sort of biofuel resources. **Figure 1.2** briefly illustrates the stages that are needed to feed the bCHP system with biomass pellet. It starts with harvesting biomass then supplying the manufacturers with feedstock for producing pellets. After that bCHP facilities are supplied with the fuel in order to operate the plant.

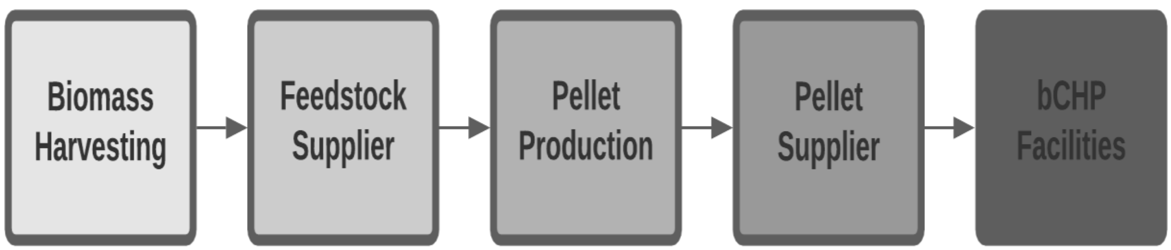

Figure 1.2 Biomass pellets supply system to feed the biomass-based CHP facilities.

CHAPTER II

LITERATURE REVIEW

In this section, the essential objective is to introduce the existing research studies that are related to the resilience and reliability of CHP systems, electric power systems, and engineering infrastructure. To date, many research studies have been proposed in the field of engineering systems resilience and reliability; however, a few research studies have presented reliability and resilience modeling for CHP systems. Haghifam & Manbachi, 2011 developed a model for assessing a CHP system reliability and availability based on the continuous Markov and the state-space technique. Naderipour et al., 2020 developed a method using PSO, particle swarm optimization, to optimally allocate CHP systems in microgrids endeavoring for various improvements, including improving reliability. Costa and Fichera, 2014 proposed an optimization method based on a mixed-integer linear programming, MILP, for optimally sizing a CHP system. Mrino et al., 2018 studied the effect of renewable resources variability on the operation of microgrid system through a chance-constrained stochastic mixed integer linear programming model.

Furthermore, biomass supply, which is the fuel of the system in this thesis, is in important factor that can impact the operation and resilience of the bCHP system. Various existing bodies of literature studied the biomass supply. For instance, Marufuzzaman et al., 2014 also developed a model using a mixed-integer linear programming in order to design a a biomass supply chain network considering various disruption factors, such as hurricanes and drought. Quddud et al., 2018 studied the impacts of biomass seasonality and uncertainty on pelleting process by utilizing a mixed-integer linear programming approach. Marufuzzaman and Eksioglu, 2017 developed a model using a mixed-integer linear programming in order to manage congestion in supply chains through a real-life case study, a biomass supply chain network in Southern United States.

Moreover, various existing bodies of literature that are related to Bayesian Network approaches, which being applied in this research paper, with applications on assessing different engineering systems industries, decision-making problems, and risk assessment problems. Bayesian network approach has been widely implemented in various fields, including reliability and resilience of engineering systems and infrastructure and complex decision-making problems as well. In the field of assessing and quantifying the resilience of infrastructure, Johansen & Tien, 2017 used a BN-based approach in order to quantify and assess the resilience of complex interdependencies, including service provision, geographic, and access interdependencies, amongst infrastructure systems to increase and improve their resilience. They used a real interdependent network, water, power, and gas network, in Memphis, TN, as a case study to employ the BN- based approach. Yu et al., 1999 implemented the BN approach to quantify the reliability of a power system through a case study. Hossain et., 2020 also developed a BN model in order to assess the critical interdependencies between inland port infrastructure and supply chain network. They used Port of Vicksburg in Mississippi as a case study and identified its various potential disruptions, collected historical data, and assessed how any of these disruptions could interrupt the port operations and affect the supply chain operations as well. Hosseini & barker, 2016 proposed a BN model in order to measure the resilience of an inland waterway port as a function of three different resilience capacities, namely, absorptive, adaptive, and restorative, and they considered the Port of Catoosa in Oklahoma a case study for their research to assess its resilience capacities. Hossain et., 2020 proposed another framework to measure the resilience of power system infrastructures in Washington DC through the BN approach. The BN approach is also used for decision-making problems. Hosseini & Sarder, 2019 proposed a BN model by which they determined the optimal location of the electric vehicle charging station, EVCS, among different alternatives. Based on expert knowledge and historical data, they identified criteria and sub-criteria for site selection, developed and validated the BN model, and selected the optimal alternative based on the results. Hossain et., al, 2019 also assessed the performance of an inland water way port through developing a BN model.

The major contributions of this thesis are to assess the resilience of biomass-based combined heat and power system through a case study of a power plant in Mississippi and to provide a real-life problem and application to illustrate how effective, efficient, and useful the BN approach is on assessing engineering systems resilience. This study distinguishes and differs from other CHP studies by which the resilience of CHP systems has not been considered through the BN method by previous studies. There are several existing research studies related to CHP systems considering the reliability, availability, efficiency, and determining the optimal allocation and capacity for CHP systems. Moreover, the BN approach has been implemented widely for assessing the resilience of engineering systems and infrastructures, but not biomass-based CHP systems.

CHAPTER III

BAYESIAN NETWORK

Bayesian Networks, BNs, are probabilistic graphical models representing complex problems and systems as networks and describe interdependences and relationships between a set of random variables via a directed acyclic graph, DAG, based on Bayes' theory (Fenton & Neil, 2019; Stephenson, 2000). The BN is an effective and useful tool for assessing risk and decision making, and it is constructed based on experts' and scientists' knowledge and historical data, whereas they determine the causality relationships among the variables. One of the features of BN is that the posterior probabilities of unknown variables have the ability to be updated once new evidence is provided and observed. The BNs are basically comprised of two elements: *nodes* and *arcs*. The nodes represent the variables in a network, and *arcs* link the variables and show the interconnections between them (Fenton & Neil, 2019). In BNs, nodes can be categorized into three types: *root* or *parent* nodes, *intermediate* nodes, and *child* or *leaf* nodes. The root nodes are primary in a network and independent. However, the leaf nodes are dependent, and they depend on the root nodes. In addition, intermediate nodes are the connection between the root and leaf nodes in BNs (Hosseini & Sarder, 2019; Abimbola & Khan, 2019). Furthermore, every variable or node in the BN is correlated with a conditional probability table, CPT, that determines the strength level of every interdependency (Chen & Pollino, 2012)

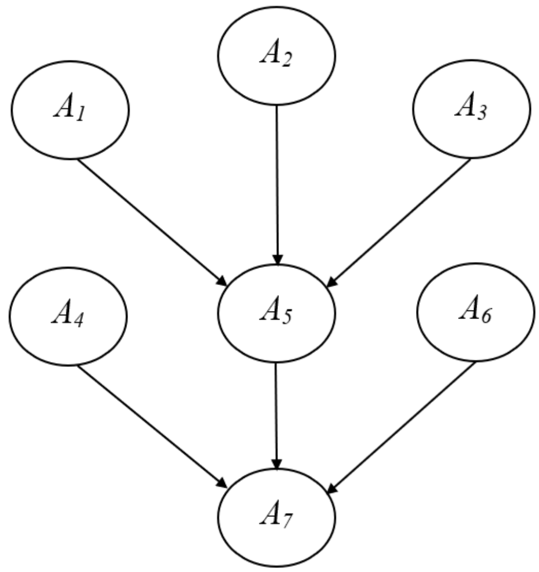

Figure 3.1 A BN example with seven nodes.

Figure 3.1 is an example of BN with seven nodes representing seven variables. Nodes A_1, A_2, A_3, A_4, and A_6 are called root nodes, and they are independent in the network. On the contrary, node A_7 is called the leaf node because it depends on A_4, A_5, and A_6. Node A_5 is an intermediate node; it links nodes A_1, A_2, and A_3 with node A_7. Additionally, arcs in **Figure 3.1** demonstrate the relationships among the seven nodes. The arc that is outgoing from node A_1 to node A_5 indicates the relationship type between them. It shows that A_5 depends on A_1.

Equation (3.1) shows the general expression of a BN comprising of n variables A_1, A_2, $A_3, \ldots, A_n$ for the full joint probability distribution.

$$P(A_1, A_2, \ldots . A_n) = P(A_1 | A_2, \ldots . A_n) P(A_2 | A_3, \ldots . A_n) \ldots$$
$$P(A_{n-1} | \, A_n) \, P(A_n) = \prod_{i=1}^{n} P(A_i \, | A_{i+1}, \ldots ., A_n) \tag{3.1}$$

Since the root, intermediate, and leaf nodes are known in **Figure 3.1,** equation (3.1) can be simplified to equation (3.2).

$$P(A_1, A_2, \dots, A_7) = P(A_1)P(A_2)P(A_3)P(A_4)P(A_6)P(A_5|A_1, A_2, A_3)P(A_7|A_4, A_5A_6) \quad (3.2)$$

The join probability of $P(A_1, A_2, \dots, A_7)$ can be found once the five unconditional probabilities, which are $P(A_1)P(A_2)P(A_3)P(A_4)P(A_6)$, are determined as well as the two conditional probabilities, which are $P(A_5|A_1, A_2, A_3)P(A_7|A_4, A_5A_6)$.

One of the essential features of BNs is the ability to update belief propagation $P(A_n)$ once some evidence is identified. For instance, once an evidence e is identified, the conditional probability for variable A_7, ($e = \{A_1, A_2, A_3, A_4, A_5, A_6, A_7\}$), can be calculated using equation (3.3).

$$P(A_7|e) = \frac{P(A_1,A_2,A_3,A_4,A_5,A_6,A_7)}{P(A_1,A_2,A_3,A_4,A_5,A_6)} = \frac{P(A_1,A_2,A_3,A_4,A_5,A_6,A_7)}{\sum_{A_7} P(A_1,A_2,A_3,A_4,A_5,A_6)} \quad (3.3)$$

By considering conditional interdependencies, equation (3) can be calculated more proficiently using equation (3.4).

$$P(A_7|e) = \frac{P(A_7|A_4,A_5.A_6)P(A_5|A_1, A_2, A_3)}{\sum_{A_7} P(A_7|A_4,A_5, A_6)P(A_5|A_1, A_2, A_3)} \quad (3.4)$$

For more details regarding the Bayesian theorem, (Fenton & Neil, 2019) is recommended for the interested readers.

CHAPTER IV

THE PROPOSED BN FRAMEWORK FOR RESILIENCE ASSESSMENT FOR BIOMASS-BASED COMBINED HEAT AND POWER SYSTEM

The proposed 4-phase framework of a bCHP resilience assessment is demonstrated in **Figure 4.1**. The details of these four phases are discussed below:

- **Phase I:** the first phase contains three steps, which are identifying the factors and sub-factors that may affect the resilience of bCHP system, identifying the relationships and interdependencies among the factors and sub-factors, and collecting data that are correlated with the identified factors and sub-factors.
- **Phase II:** the second phase is constructing the BN model utilizing a BN software called AgenaRisk.
- **Phase III**: once the model is built, the third phase is to run a sensitivity analysis to validate the model.
- **Phase VI:** the final phase is to analyze and assess the results. This step can be beneficial and helpful to enhance and develop a strategic plan to deal with potential risks that may disrupt the bCHP.

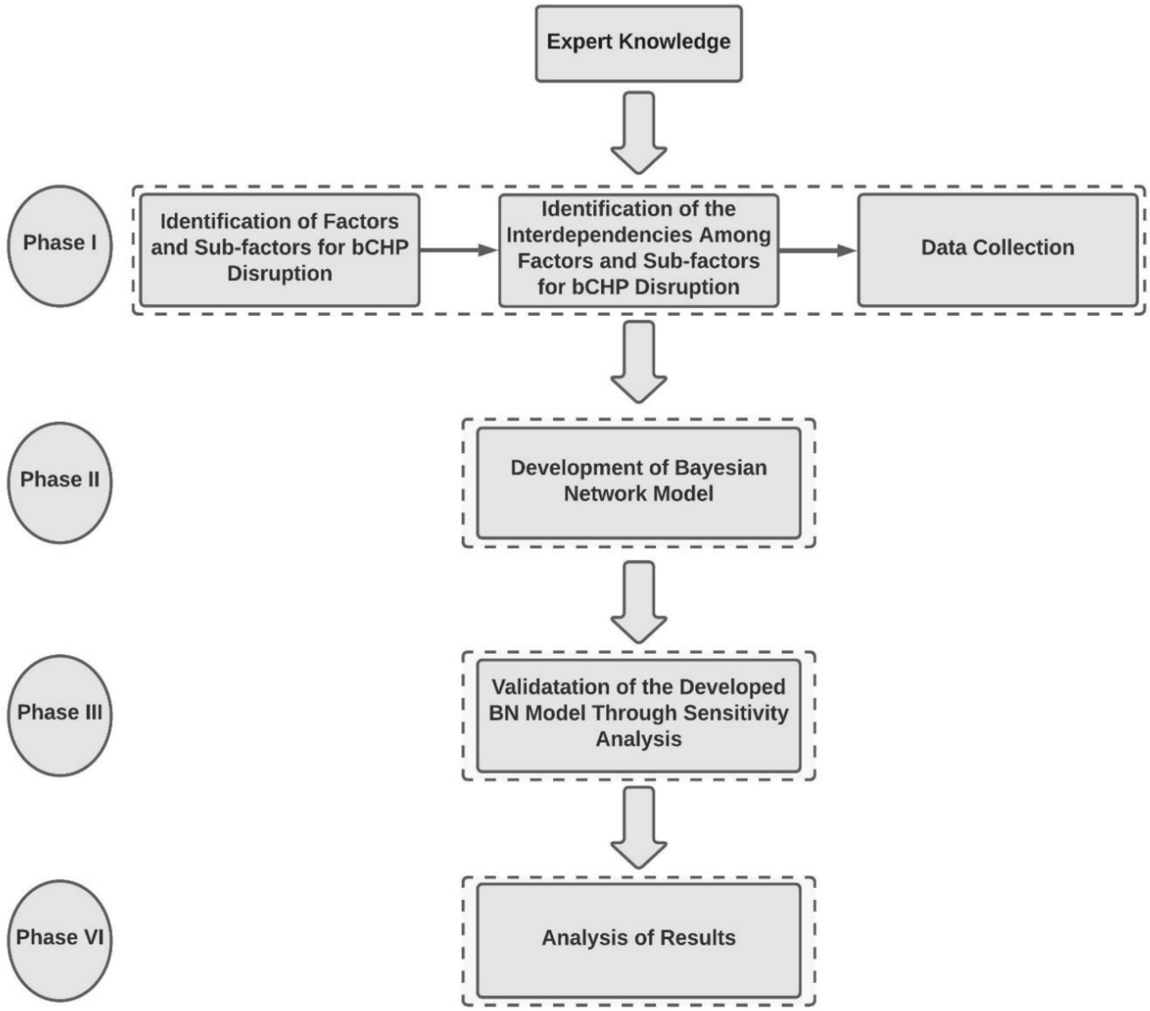

Figure 4.1 The proposed 4-phase framework for assessing bCHP resilience.

CHAPTER V

DESCRIPTION OF FACTORS AND DEVELOPMENT OF BN MODEL

Identifying factors and sub-factors for assessing the resilience of bCHP is an essential step in this paper. We describe factors pertaining to bCHP resilience from four perspectives, namely, technical, human factors, and environmental factors. Furthermore, sub-factors that are related to the main factors are also considered and taken into account. **Figure 5.1** illustrates the factors and sub-factors considered for assessing bCHP resilience. The details of the sub-factors are addressed below.

5.1 Technical Factors:

Six sub-factors are considered under the technical factors, namely, interruption of biomass fuel supply, bCHP equipment failure, bCHP periodic maintenance, suppliers performance, suppliers availability and variability, and biomass fuel availability and variability. The details of the sub-fact are addressed below.

5.1.1 Interruption of Biomass Fuel Supply:

This sub-factor refers to the risk of interruption of pellet supply, which is the needed fuel to operate the bCHP. A reliable and continuous pellet supply is essential to increase the resilience of the bCHP system; however, the interruption of the pellet supply causes interruptions of generating electrical power and producing thermal energy, especially for CHP plants that do not support dual-fuel capable systems. Pellet supply can be interrupted due to many factors in

Mississippi, such as extreme weather events. A resilient bCHP system requires an interrupted pellet supply.

5.1.2 Modeling of Interruption of Biomass Fuel Supply:

In order to model the interruption of biomass fuel supply, a NoisyOR function is used to compute the posterior probability. An example to illustrate NoisyOR function is that if n Boolean variables $X_1, X_2, \dots . X_n$ are conditioned on $\boldsymbol{A}$, and the probability of $\boldsymbol{A}$ is True when only one of the Boolean variables is true. The NoisyOR function is shown in Equation (5.1) where X_n represents the Boolean variable, v_n represents the weight associated with X_n, between 0 and 1, and l refers to the leak factor, which represents some other hidden factors that contribute to the leaf node being true (Fenton & Neil, 2019).

$$A = NoisyOR(X_1, v_1, X_2, v_2, \dots . , l) \tag{5.1}$$

The modeling equation of the interruption of biomass fuel supply is presented in Equation (5.2).

$$\begin{aligned} &The\ interruption\ of\ biomass\ fuel\ supply \\ &\qquad = NoisyOR(Extreme\ weather\ events, 0.1, 0.1) \end{aligned} \tag{5.2}$$

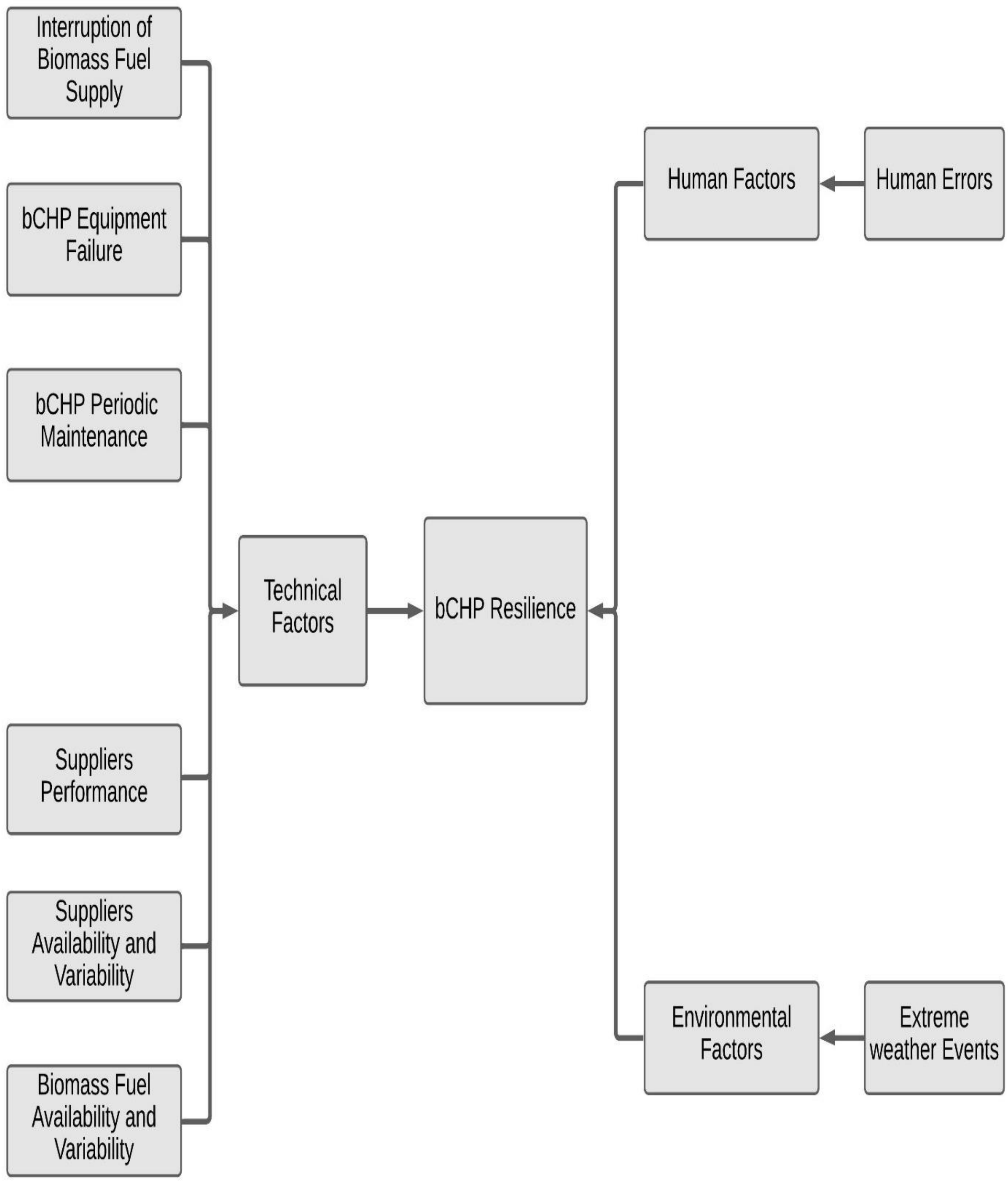

Figure 5.1 Factors and sub-factors for biomass-based CHP resilience assessment.

5.1.3 bCHP Equipment Failure:

This sub-factor refers to the potential failure of the bCHP system and its components. If they occur, they will prevent the operation of the system. Thus, that may result in a complete shutdown of a bCHP system. Two main factors contributing to the bCHP equipment failure, namely, human errors and other sub-factors, including manufacturing defects and aging equipment and systems.

5.1.4 Modeling of bCHP Equipment Failure:

The modeling equation of bCHP equipment failure is presented in Equation (5.3).

$$bCHP\ equipment\ failure = NoisyOR(Human\ errors, 0.1, Other\ subfactors, 0.1, 0.1) \tag{5.3}$$

5.1.5 bCHP Periodic Maintenance:

Malfunctions are subject to occur in any system, and they can be both predictable and unpredictable. Operational failures due to the lack of periodic maintenance affect the resilience of bCHP system. In order to avoid this situation, immediate repair and periodic maintenance would be needed. The lack of an efficient on-site repair and periodic maintenance service is one of the sub-factors that degrade bCHP resilience. Periodic Maintenance is addressed in terms of on-time repair and spare parts availability.

5.1.6 Modeling of bCHP Periodic Maintenance:

Two main variables, known as continuous variables, contributing to the periodic maintenance, which are on time repair and availability of spare parts. The modeling of a bCHP periodic maintenance and its contributors are shown in **Table 5.1** and **Table 5.2**.

Table 5.1 Modeling of variables contributing to periodic maintenance.

Variable name	Modeling technique	Modeling description
On-time repair	TNORM (μ=0.85, α^2=0.02, LB=0.65, UB=0.95)	We assumed that on time repair follows a t normal distribution with a mean of 0.85, a variance of 0.02, best case of 95% and worst case of 0.65.
Availability of spare parts	TNORM (μ=0.90, α^2=0.03, LB=0.8, UB=1)	We approximately assumed that spare parts are available with a mean of 0.9, a variance of 0.03, and lower bound and upper bound of 0.8 and 1, respectively.

Table 5.2 Modeling of periodic maintenance variable.

Variable name	Modeling technique	Modeling description
bCHP periodic maintenance	If (on time repair ≥0.85&& availability of spare parts ≥ 0.85, “True”,” False”)	If the on-time repair is equal or more than 85% and the availability of spare parts is more than 85%, the bCHP periodic maintenance is labeled (True), otherwise, (False)

5.1.7 Supplier Performance:

This sub-factor refers to supplier’s ability to feed the bCHP system with biomass pellets fuel within the predefined delivery schedule. It is obvious that the more efficient the supplier is, the more resilient the bCHP system is. Supplier performance is addressed in terms of lead time and on-time delivery, and it can be affected by extreme weather events as well.

5.1.8 Modeling of Supplier Performance:

Two main continuous variables contributing to the periodic maintenance besides extreme weather events, which are on time delivery and lead time. The modeling of bCHP supplier performance and its contributors are shown in **Table 5.3** and **Table 5.4**.

Table 5.3 Modeling of variables contributing to supplier performance.

Variable name	Modeling technique	Modeling description
Lead time	TNORM (μ=10, α^2=0.05, LB=6, UB=15)	According to (Hossain et al., 2020), the lead time of biomass supply chain follows a TNORM distribution with a mean of 10 days, an estimated variance of 0.05, and lower and upper bound of 15 days and 6 days, respectively.
On-time delivery	TNORM (μ=0.95, α^2=0.0005, LB=0.9, UB=1)	On-time delivery follows a TNORM distribution with a mean delivery rate of 0.95, a variance of 0.0005, and lower and upper bound of 0.90 and 1 rate, respectively (Hossain et al., 2020).

Table 5.4 Modeling of supplier performance variable.

Variable name	Modeling technique	Modeling description
Supplier performance	If (Lead time<=15&& on time delivery>=0.90, && extreme weather events == "False", "True"," False")	If the lead time is less than 16 days, on-time delivery rate is more than 0.9, and the extreme weather events do not occur, the supplier performance is labeled (True); otherwise, (False). It is assumed that on-time delivery and lead time are weighted equally by 45%, and the extreme weather events are weighted by 10%.

5.1.9 Supplier Availability and Variability:

This sub-factor refers to the availability of biomass suppliers around the plant. Since the used fuel of the CHP is biomass pellets, CHP resilience significantly depends on the availability of biomass pellets. Suppliers variability is an important factor as well. It increases the reliability of feeding the plant in case the main supplier fails to feed the cogeneration plant with the fuel. Hence, the more available and variable suppliers, the more resilient the bCHP is.

Table 5.5 shows the biomass pellet manufacturers that are located within 300 miles around the plant in Mississippi, Alabama, and Louisiana.

Table 5.5 Biomass pellet suppliers.

Biomass pellet supplier	State	Distance to the plant
Enviva Pellets Lucedale LLC	Mississippi	69 mi
Enviva Pellets Amory	Mississippi	285 mi
Drax Biomass Inc. Amite Bioenergy	Mississippi	167 mi
Alabama Pellets LLC	Alabama	205 mi
Zilkha Biomass Selma	Alabama	248 mi
Westervelt Renewable Energy, LLC	Alabama	254 mi
Drax Biomass Inc. Morehouse Bioenergy	Louisiana	296 mi
Drax Biomass Port	Louisiana	137 mi
Drax Biomass Lasalle Bio Energy	Louisiana	286 mi

5.1.10 Modeling of Supplier Availability and Variability:

Table 5.6 shows the modeling of the suppliers availability in the study area.

Table 5.6 Modeling of the availability of biomass pellet suppliers.

Variable name	Modeling technique	Modeling description
Suppliers availability	If (biomass pellet suppliers > 3 suppliers, “True”,” False”)	If the biomass pellet suppliers are more than 3, the suppliers availability is labeled (True), otherwise, (False).

5.1.11 Biomass Fuel Availability and Variability:

This sub-factor refers to the availability and variability of biomass feedstocks in Harrison county, where Plant Watson is located, and in its neighbor counties, namely, George county, Hancock county, Pearl River county, and Stone county. According to the National Renewable Energy Laboratory, NREL, **Table 5.7** illustrates the biomass feedstock production in each county and how many types are available.

Table 5.7 Biomass feedstock availability and variability in the study area.

County	Number of feedstock types	Feedstock Production (Tons/Year)
Harrison County	14 types	53,664.37
Jackson County	13 types	66,795.77
George County	13 types	62,737.83
Hancock County	13 types	25,394
Pearl River County	13 types	152,649.28
Total Production in All Counties	14 types	435,188.5

5.1.12 Modeling of Biomass Fuel Availability and Variability:

One main variable contribution to the biomass fuel availability, which is feedstock production. The modeling of feedstock production is shown in **Table 5.8**, and the modeling of biomass fuel availability is shown in **Table 5.9**.

Table 5.8 Modeling of feedstock production in the study area.

Variable name	Modeling technique	Modeling description
Feedstock production	Triangle (37565, 53664, 69763)	The feedstock production in the study area follows a triangle distribution with estimated minimum and maximum values of 37,565 and 69,763, respectively, and the most likely value is 53,664 tons/year.

Table 5.9 Modeling of biomass feedstock availability and variability in the study area.

Variable name	Modeling technique	Modeling description
Biomass fuel availability	If (feedstock production>=50,000, "True"," False")	If the feedstock production is more than 50,000 tons per year, biomass fuel availability is labeled (True); otherwise, (False).

5.2. Environmental Factors:

Environmental factors are the aspects that may have negative impacts on the resilience of bCHP in its physical environment in Mississippi State. Environmental factors include one main sub-factors, which is extreme weather events, including hurricanes and tornadoes.

5.2.1. Extreme Weather Events:

This sub-factor refers to the natural disasters that occur commonly in Mississippi. Since some natural disasters, such as hurricanes and tornados, are inevitable and common in Mississippi, the bCHP is vulnerable to disruptions. Moreover, one of the most primary reasons for power outages in the United States of America is severe weather (President's Council of Economic Advisers and the U.S. Department of Energy's Office of Electricity Delivery and Energy Reliability, 2013). Indeed, many CHP systems have proved their high resilience and reliability through extreme weather events in many areas. However, natural disasters may still affect the bCHP, biomass fuel supply, and supplier performance.

5.2.2. Modeling of Extreme Weather Events:

5.2.2.1. Hurricanes:

About 10 major hurricanes hit Mississippi from 2000 to 2020 with an average of 0.47. In addition, some of these hurricanes were severe hurricanes, such as Hurricane Katrina in 2005, and it caused extreme economic costs estimated from $160 billion to $250 billion according to (Amadeo, 2020). **Table 5.10** shows the major and effective hurricanes that hit Mississippi.

Table 5.10 Major hurricanes hit Mississippi from 2000 to 2020.

Hurricane	Category	Year
Isidore	3	2002
Cindy	1	2005
Dennis	4	2005
Rita	5	2005
Katrina	5	2005
Humberto	3	2007
Irma	5	2017
Nate	1	2017
Barry	1	2019
Zeta	2	2020

In order to find the probability of hurricanes, the Poisson distribution function is used as represented in the following equation (5.4) (Bhusal et al., 2020).

$$P(h = x) = \frac{exp(-\lambda) \times \lambda^h}{x!} \tag{5.4}$$

Where P represents the probability of annual occurrence of hurricanes, λ represents the mean or the average number of hurricanes, h represents the number of hurricanes per year, and x represents the number of occurrences. Thus, based on the historical data represented in **Table 5.10**, the probability one hurricane occurs is about 27%.

5.2.2.2. Tornadoes:

During the last 20 years, about 171 strong and violent tornadoes, ranging from F2 to F5 tornadoes, hit Mississippi State with an average of 8.55 per year (NWS). **Table 5.11** shows the major and effective tornadoes that hit Mississippi.

Table 5.11 Number of tornadoes in Mississippi State from 2000 to 2019 (NWS).

	Tornadoes				
Year	**F2**	**F3**	**F4**	**F5**	**Total**
2000	2	1	0	0	3
2001	4	3	2	0	9
2002	2	1	0	0	3
2003	3	1	0	0	4
2004	8	2	0	0	10
2005	12	2	0	0	14
2006	3	2	0	0	5
2007	4	0	0	0	4
2008	9	5	0	0	14
2009	4	0	0	0	4
2010	11	2	1	0	14
2011	15	12	1	2	30
2012	8	2	0	0	10
2013	4	1	1	0	6
2014	5	4	1	0	10
2015	1	0	0	0	1
2016	5	0	0	0	5
2017	9	1	0	0	10
2018	3	0	0	0	3
2019	11	1	0	0	12

The probability of 8 or less tornadoes occur in Southern Mississippi is calculated by using Poisson distribution function as well, and the result is about 51%.

Table 5.12 Modeling of extreme weather events.

Variable name	Modeling technique	Modeling description
Extreme Weather Events	If (hurricanes || tornadoes== “True”, “True”,” False”)	If any hurricanes or tornadoes occur, the extreme weather events are labeled (True); otherwise, (False)

5.3. Human Factors:

Human factors can be defined as the interrelationship between the bCHP and the staff, and it includes human errors.

5.3.1. Human Errors:

One of the main factors affecting the bCHP resilience is equipment and operational failures. There are various reasons leading to malfunction, and one of these reasons is personnel errors in the workplace.

5.3.2. Modeling of Human Errors:

Based on a research study by (Morais et al., 2018), the probabilities of human execution errors in different industry areas are 8.99% for wrong-time errors, 7.36% for wrong-type errors, and 1.09% for wrong place errors. Therefore, it can be assumed that there is an 8.99% chance that wrong-time errors happen, a 7.63% chance that wrong type errors occur, and a 1.09% chance that wrong place errors happen during operating a bCHP system.

Table 5.13 Modeling of human errors.

Variable name	Modeling technique	Modeling description
Human Errors	If (wrong-time errors == "True" || wrong-place errors == "True" || wrong-type errors == "True", "True"," False")	If any type of human errors occurs, human errors are labeled (True); otherwise, (False).

5.4. Modeling of the bCHP Resilience:

The final target node in the BN model, the bCHP resilience variable, provides the result of bCHP resilience, and it is conditioned on three main factors, namely, technical factors, environmental factors, and human factors. The three main factors are associated with three different weights, 60%, 30%, and 10%, respectively. As illustrated in **Figure 5.2**, the probability of the resilience of bCHP being true or sufficient is 70.4%

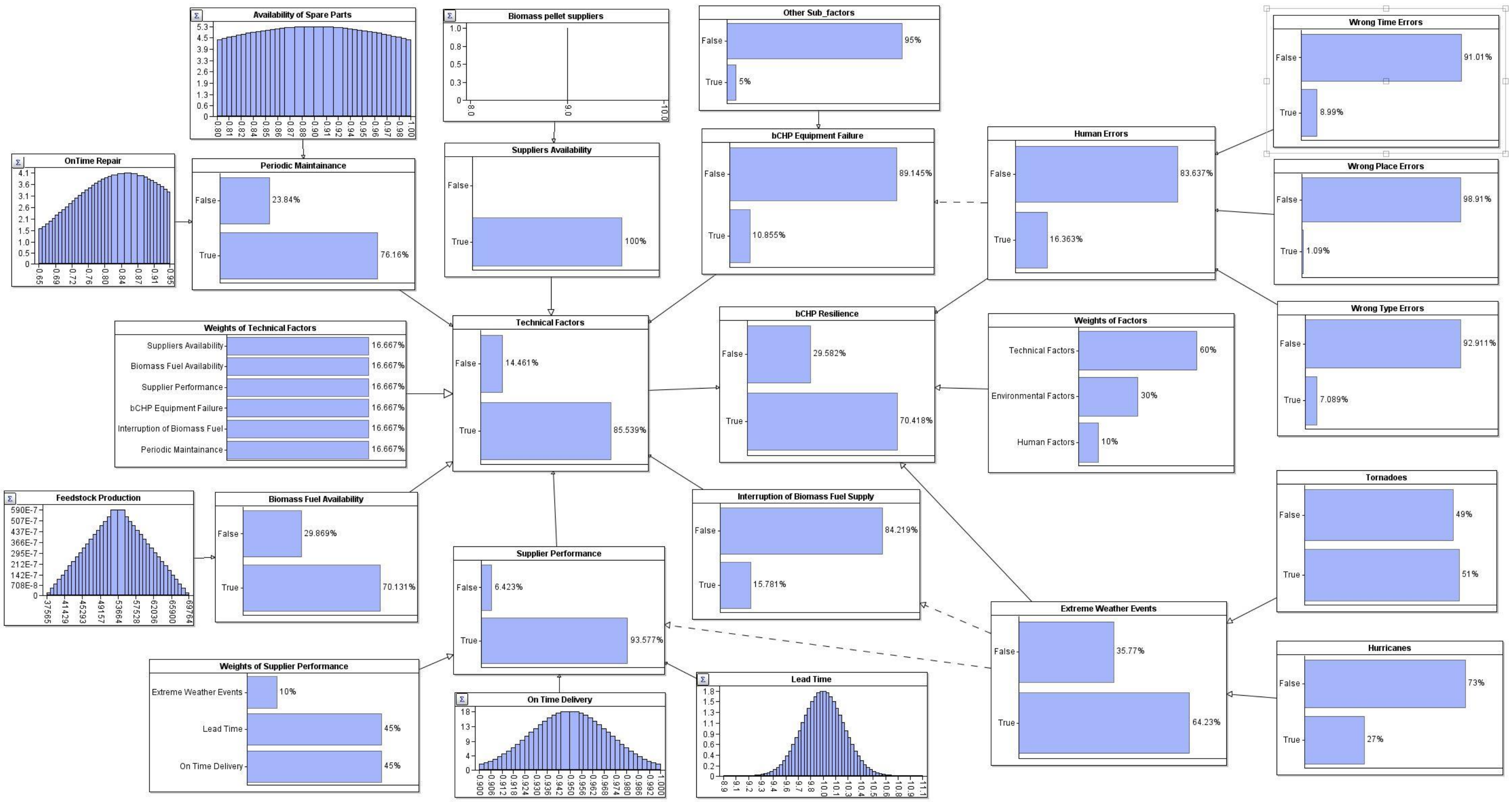

Figure 5.2 The base model of the BN for measuring the resilience of bCHP system.

CHAPTER VI

RESULTS AND ANALYSIS

In this section, we will introduce and perform three different types of analysis on the BN model, such as sensitivity analysis and belief propagation analysis.

6.1 Sensitivity Analysis:

Sensitivity analysis is an effective tool that can be implemented in order to validate an expert-built model. Performing sensitivity analysis allows to diagrammatically represent the impacts of a set of selected nodes on the target node or on any selected node. Moreover, it allows decision-makers to determine how sensitive their results are (Fenton & Neil, 2019). To gain more understanding of the BN model, and to determine what variables have more impact on the bCHP resilience, the sensitivity analysis is performed on the BN model using AgenaRisk software.

The sensitivity analysis is performed on bCHP resilience as a target node with respect to its contributing variables, namely, extreme weather events, supplier performance, interruption of biomass fuel supply, biomass availability, human errors, periodic maintenance, and suppliers availability. The sensitivity analysis of the resilience of the bCHP is diagrammatically shown in **figures 6.1 and 6.2**, in the form of a tornado graph. The sensitivity of each node can be determined based on the length of the bars, where the longer the bar is, the more impactful the node is (Lawrence et al., 2020). **Figure 6.1** demonstrates the impact of the selected factors and sub-factors on the bCHP resilience when bCHP resilience is labeled “True”. However, **Figure 6.2** demonstrates the impact of those factors and sub-factors on the bCHP resilience when bCHP resilience is labeled “False”. It can be concluded from both figures that extreme weather events have the highest impact and periodic maintenance has the lowest impact on the resilience of bCHP system. The figures show that the probability of bCHP resilience given extreme weather events increases from 0.59, when the extreme weather events is “True” to 0.9 when the extreme weather events is “False”. On the contrary, the range of the impact of periodic maintenance is narrow, from 0.62 to 0.72.

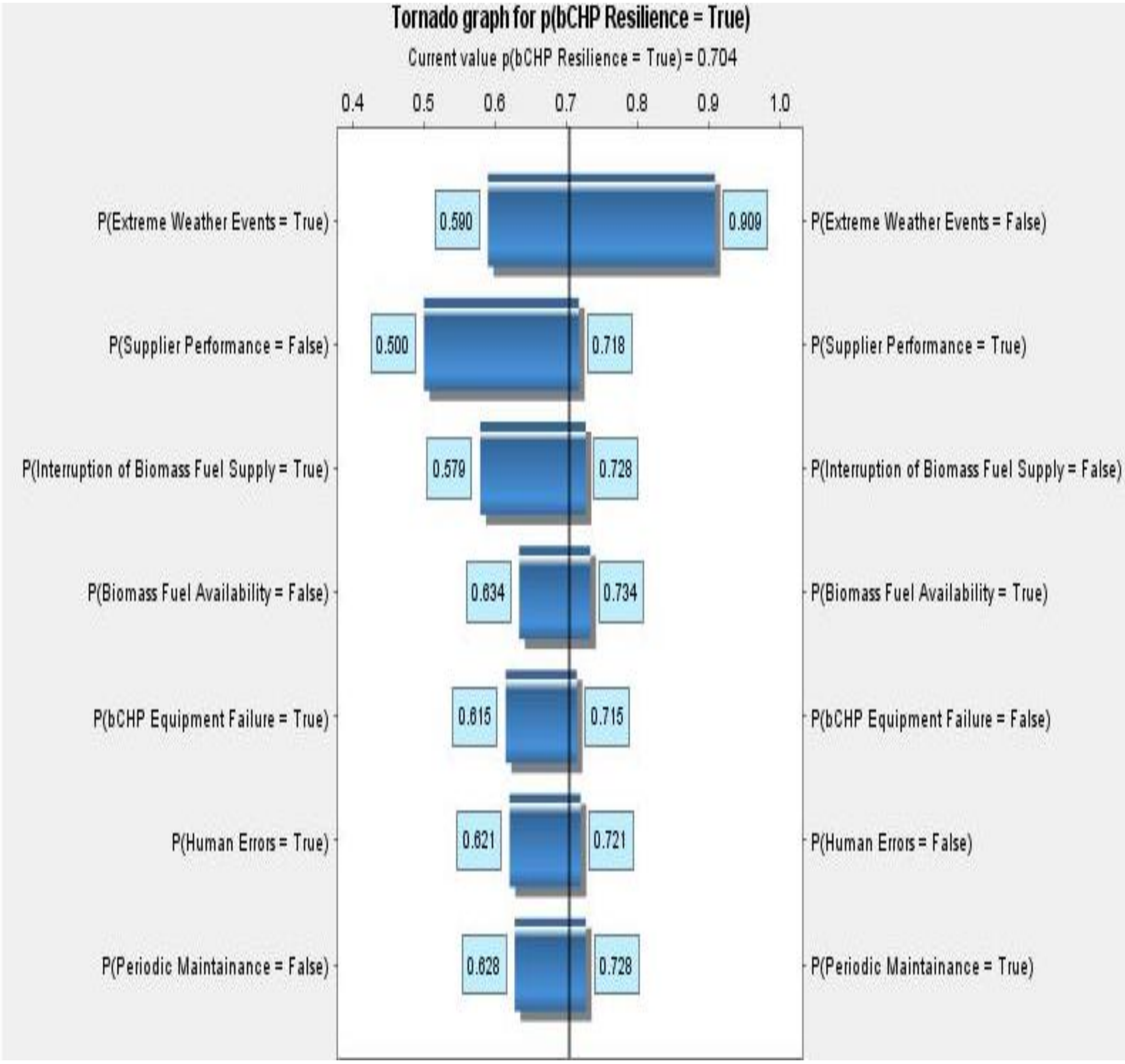

Figure 6.1 Sensitivity analysis of the resilience of bCHP: P (bCHP Resilience = True) = 70%.

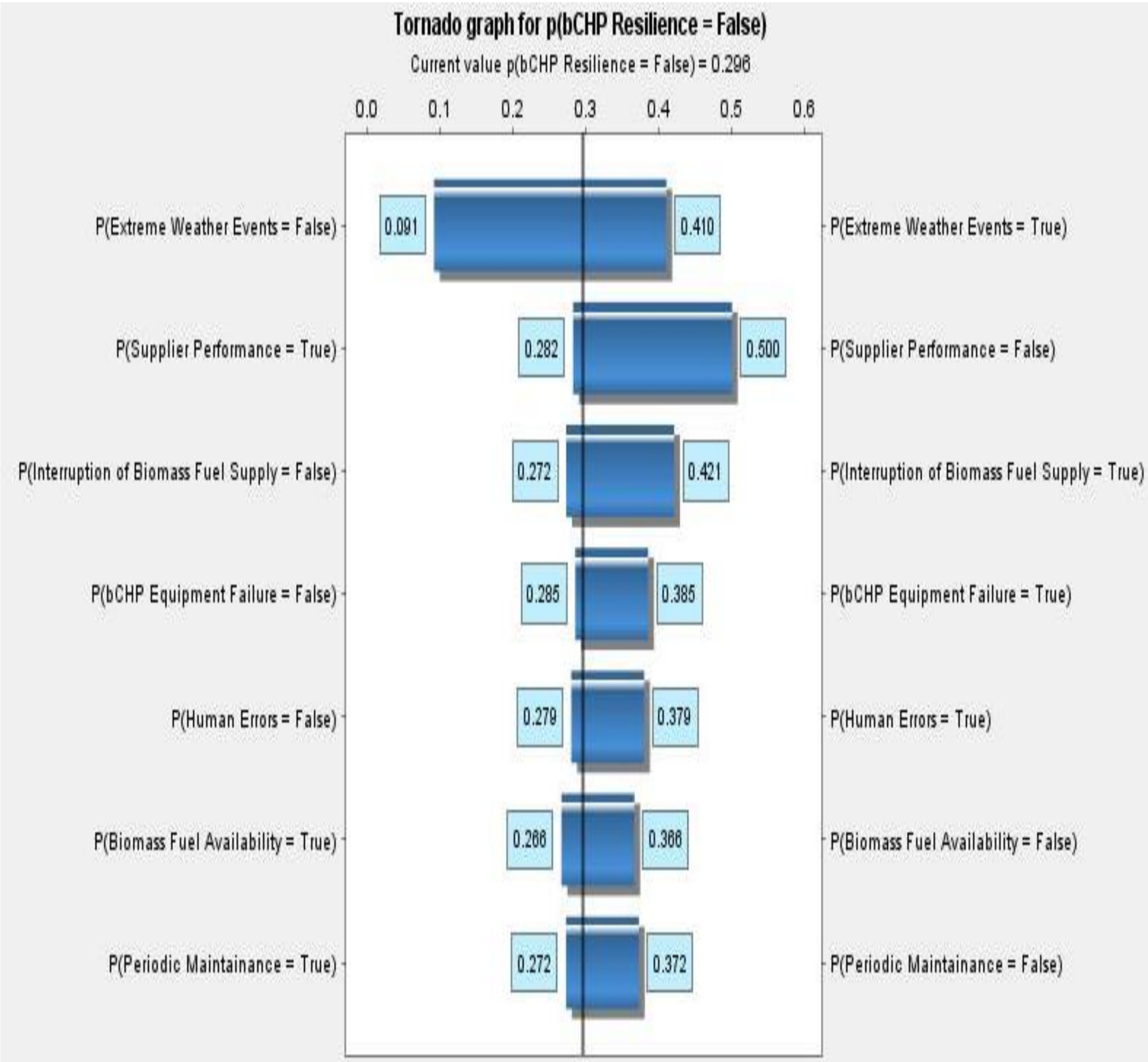

Figure 6.2 Sensitivity analysis of the resilience of bCHP: P (bCHP Resilience = False) = 29.6%.

6.2 Belief Propagation Analysis:

One of the distinct advantages and strengths of the Bayesian Network approach is the ability to perform propagation analysis that allows entering different observations in any node in the model and using propagation to compute the marginal probabilities of the other unobserved variables that depend on the observed nodes (Hosseini et al., 2016; Hossain et al., 2019). Forward propagation analysis is performed on the BN model in order to measure the impact of one or more observed variables on the child or target node, bCHP resilience. Moreover, the backward propagation analysis is performed on the BN model in order to compute the probability of intermediate and parent nodes by propagating the impact of the child node on the entire network.

In this study, two different scenarios, optimistic and pessimistic, are examined through forward propagation analysis on five variables, namely, extreme weather events, biomass fuel availability, periodic maintenance, bCHP equipment failure, and supplier performance. On the contrary, the best possible scenario or the target node is determined as well through backward propagation analysis.

Figure 6.3 illustrates an optimistic scenario for extreme weather events, which means that the extreme weather events will not occur. As a result, the resilience of bCHP system increases from 70.4% to 90.9%. On the other hand, **Figure 6.4** illustrates a pessimistic scenario for extreme weather events, which means that the extreme weather events will occur for a chance of 100%. As a result, the resilience of bCHP system decreases from 70.4% to 59%. Moreover, if the resilience of bCHP is set to 100%, as demonstrated in **Figure 6.5**, the technical factors should increase to 96.38% and human factors and extreme weather events should decrease to 14.4% and 53.8%, respectively. The other results of forward propagation analysis are summarized below:

- *Biomass Fuel Availability:* for the optimistic scenario, the resilience is 73.4%, and for the pessimistic scenario, the resilience is 63%.
- *Periodic Maintenance:* for the optimistic scenario, the resilience is 72.8%, and for the pessimistic scenario, the resilience is 62%.

- *bCHP Equipment Failure*: for the optimistic scenario, the resilience is 71.5%, and for the pessimistic scenario, the resilience is 61.5%.
- *Supplier Performance:* for the optimistic scenario, the resilience is 71.8%, and for the pessimistic scenario, the resilience is 50%.

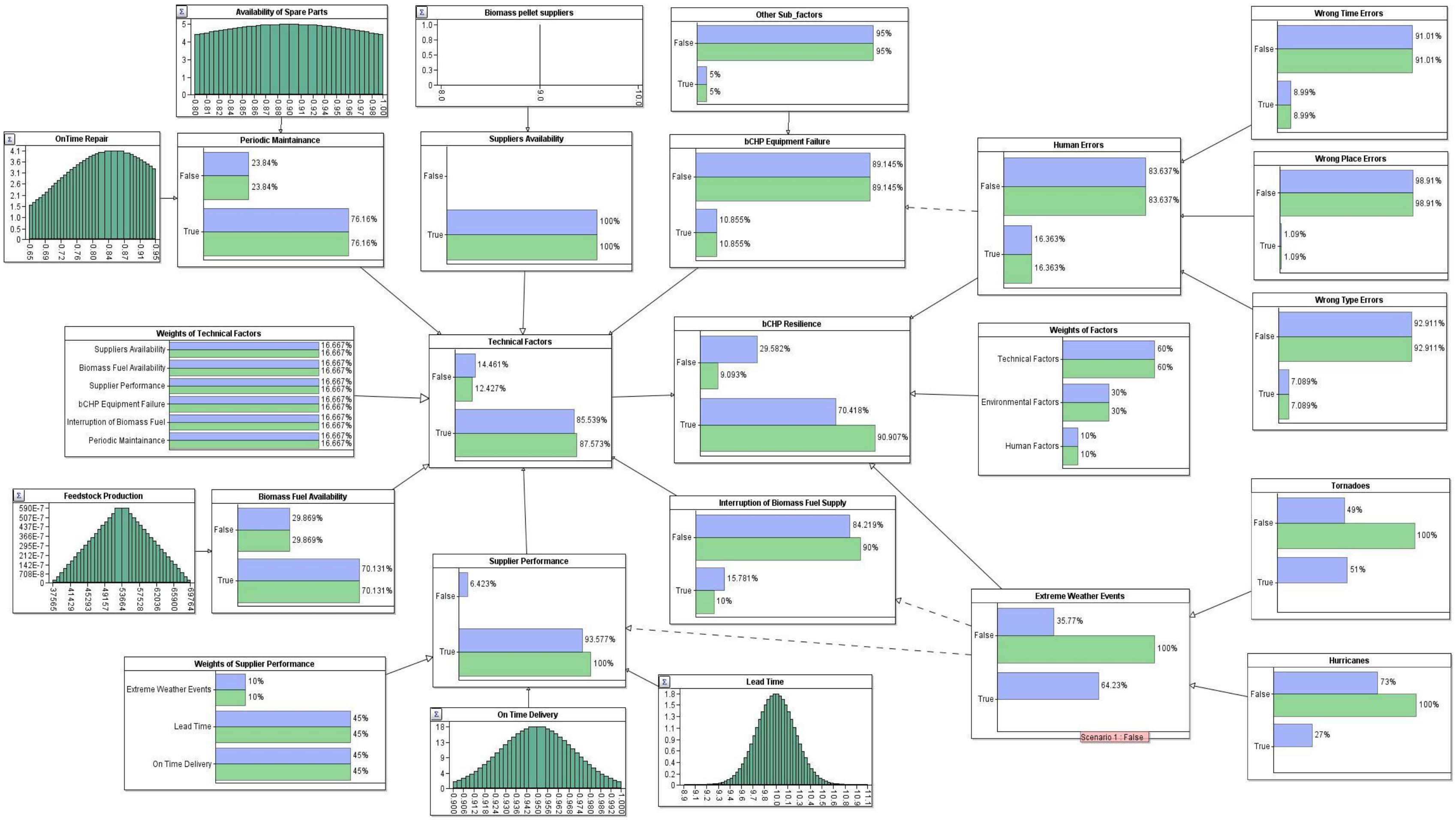

Figure 6.3 The developed BN model for the optimistic scenario of extreme weather events.

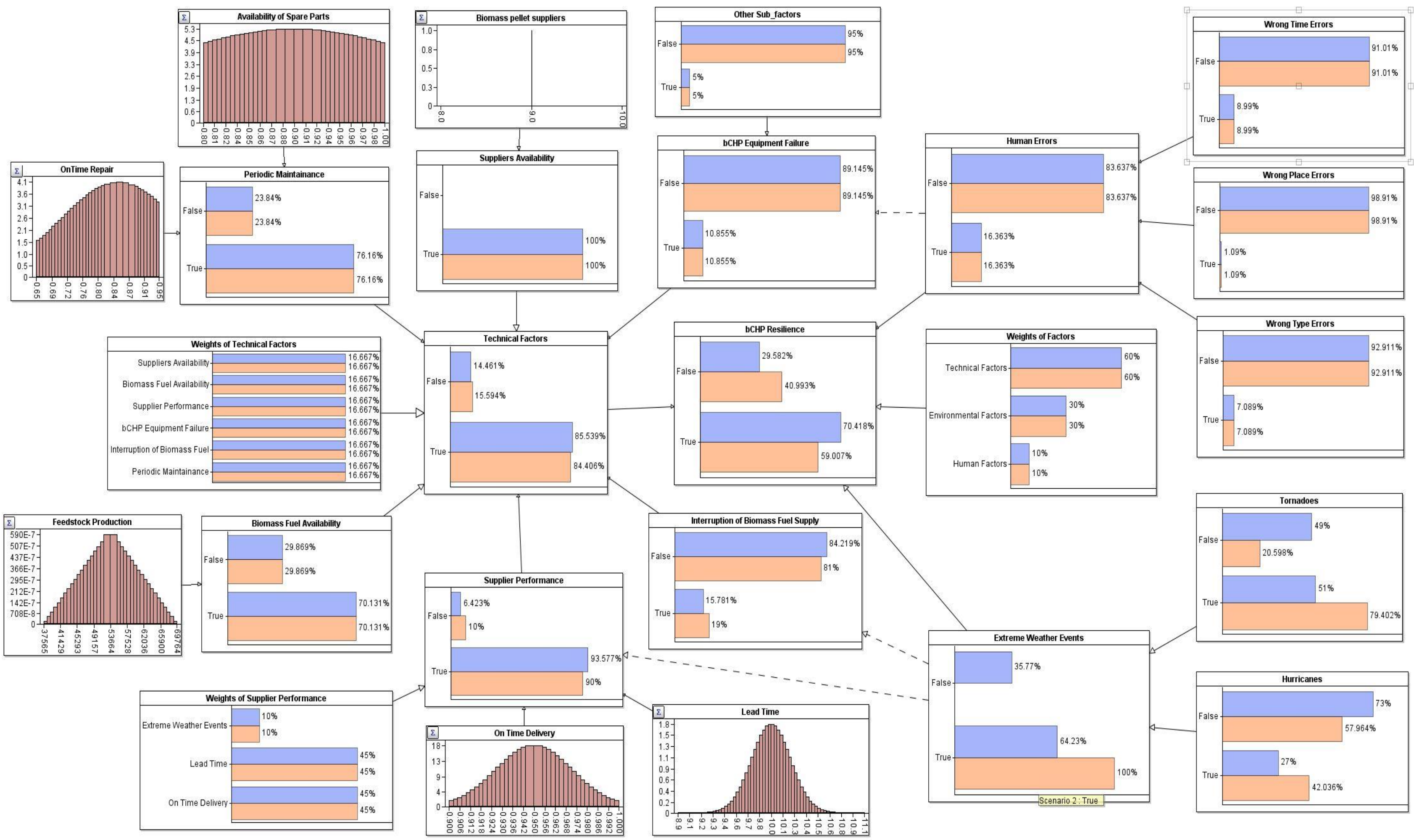

Figure 6.4 The developed BN model for the pessimistic scenario of extreme weather events.

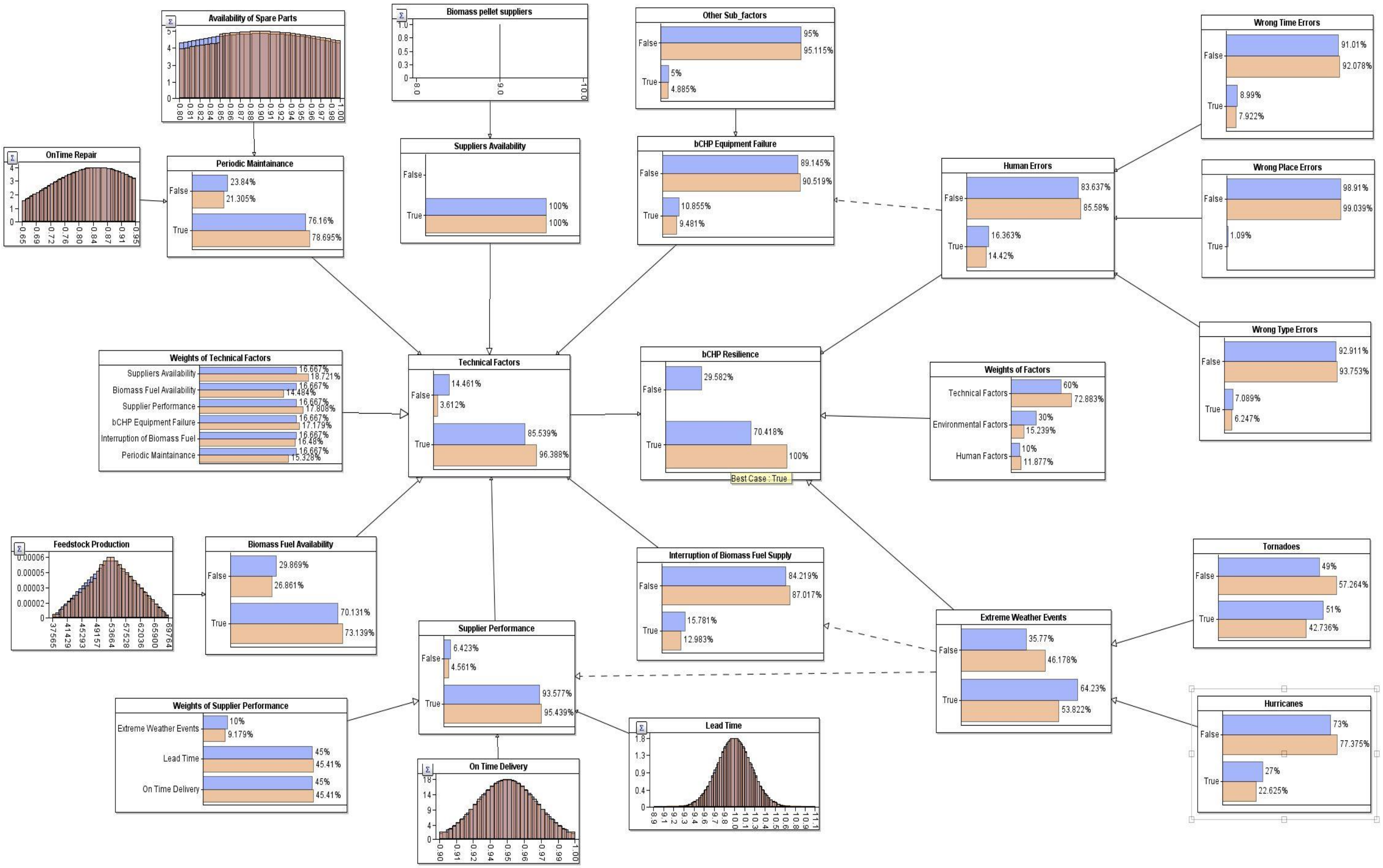

Figure 6.5 Backward propagation analysis of BN for a 100% resilience of bCHP.

CHAPTER VII

CONCLUSION AND FUTURE WORK

This study has two major contributions, which are proposing a 4-phase framework for assessing the resilience of biomass-based combined heat and power system and demonstrating the efficiency and effectiveness of the approach of Bayesian network in assessing the resilience of engineering systems and infrastructure through a real-life application. In the initial stage, three major factors associated with the resilience of bCHP system are identified; namely, extreme weather events, technical factors, and human factors, and then the causations among the factors and sub-factors are identified as well. The information and data associated with the factors and sub-factors are obtained from different research papers and official websites. In the second stage, the collected data and subjective opinions are converted into a BN model using Agenarisk software. After the development stage, the BN model then is validated through sensitivity analysis, and then optimistic and pessimistic scenarios are applied on five different variables through forward propagation analysis, and finally, the backward propagation analysis is applied by setting the resilience value of bCHP to 100% to determine the optimal values of the causal variables.

This study can be extended in various research directions. For instance, in this study, only the resilience of bCHP system is measured; however, the resilience of both the power plant station and bCHP system can be measured and quantified together in order to determine how resilience and reliable the overall plant will be.

REFERENCES

Abimbola, M., & Khan, F. (2019). Resilience modeling of engineering systems using dynamic object-oriented Bayesian network approach. *Computers & Industrial Engineering*, *130*, 108–118. https://doi.org/10.1016/j.cie.2019.02.022

Amadeo, K. (2020). *Natural Disasters' Economic Impact*. Available from. https://www.thebalance.com/cost-of-natural-disasters-3306214.

Balli, O., Aras, H., & Hepbasli, A. (2007). Exergetic performance evaluation of a combined heat and power (CHP) system in Turkey. *International Journal of Energy Research*, *31*(9), 849–866. https://doi.org/10.1002/er.1270

Bhusal, N., Gautam, M., Abdelmalak, M., & Benidris, M. (2020). Modeling of Natural Disasters and Extreme Events for Power System Resilience Enhancement and Evaluation Methods. *2020 International Conference on Probabilistic Methods Applied to Power Systems (PMAPS)*. https://doi.org/10.1109/pmaps47429.2020.9183679

Carlson, A., & Hedman, B. (2004). Assessing the Benefits of On-Site Combined Heat and Power during the August 14, 2003 Blackout. Available from: https://www.energy.gov/sites/prod/files/2013/11/f4/chp_blackout_081403.pdf

Chittum, A., & Relf, G. (2019). Valuing distributed energy resources: Combined heat and power and the modern grid. *The Electricity Journal*, *32*(1), 52–57. https://doi.org/10.1016/j.tej.2019.01.003

Chen, S. H., & Pollino, C. A. (2012). Good practice in Bayesian network modelling. *Environmental Modelling & Software*, *37*, 134–145. https://doi.org/10.1016/j.envsoft.2012.03.012

Costa, A., & Fichera, A. (2014). A mixed-integer linear programming (MILP) model for the evaluation of CHP system in the context of hospital structures. *Applied Thermal Engineering*, *71*(2), 921–929. https://doi.org/10.1016/j.applthermaleng.2014.02.051

Dong, L., Liu, H., & Riffat, S. (2009). Development of small-scale and micro-scale biomass-fuelled CHP systems - A literature review. In *Applied Thermal Engineering* (Vol. 29, Issues 11–12, pp. 2119–2126). https://doi.org/10.1016/j.applthermaleng.2008.12.004

EPA. (2012). *A Clean Energy Solution Combined Heat and Power*. Available from: https://www.epa.gov/sites/production/files/2015-07/documents/combined_heat_and_power_a_clean_energy_solution.pdf

EPA. (2017). *Catalog of CHP Technologies*. Available from: https://www.epa.gov/sites/production/files/2015-07/documents/catalog_of_chp_technologies.pdf

President's Council of Economic Advisers and the U.S. Department of Energy's Office of Electricity Delivery and Energy Reliability. (2013). *Economic benefits of increasing electric grid resilience to weather outages.* Available from: https://www.energy.gov/sites/prod/files/2013/08/f2/Grid%20Resiliency%20Report_FINAL.pdf

Fenton, N., & Neil, M. (2019). *Risk assessment and decision analysis with Bayesian networks*. (Second Edition). Chapman& Hall/CRC.

Haghifam, M. R., & Manbachi, M. (2011). Reliability and availability modelling of combined heat and power (CHP) systems. *International Journal of Electrical Power and Energy Systems*, *33*(3), 385–393. https://doi.org/10.1016/j.ijepes.2010.08.035

HOSSAIN, N. U. I., Amrani, S. el, Jaradat, R., Marufuzzaman, M., Buchanan, R., Rinaudo, C., & Hamilton, M. (2020). Modeling and assessing interdependencies between critical infrastructures using Bayesian network: A case study of inland waterway port and surrounding supply chain network. *Reliability Engineering and System Safety*, *198*. https://doi.org/10.1016/j.ress.2020.106898

Hossain, N. U. I., Jaradat, R., Hosseini, S., Marufuzzaman, M., & Buchanan, R. K. (2019). A framework for modeling and assessing system resilience using a Bayesian network: A case study of an interdependent electrical infrastructure system. *International Journal of Critical Infrastructure Protection*, *25*, 62–83. https://doi.org/10.1016/j.ijcip.2019.02.002

Hossain, N. U. I., Jaradat, R., Marufuzzaman, M., Buchanan, R. K., & Rinaudo, C. (2019). Assessing and enhancing oil and gas supply chain resilience: A Bayesian network based approach. *IISE Annual Conference and Expo 2019, May*.

Hossain, N. U., Nur, F., Jaradat, R., Hosseini, S., Marufuzzaman, M., Puryear, S. M., & Buchanan, R. K. (2019). Metrics for Assessing Overall Performance of Inland Waterway Ports: A Bayesian Network Based Approach. *Complexity, 2019*, 1–17. https://doi.org/10.1155/2019/3518705

Hosseini, S., & Barker, K. (2016). Modeling infrastructure resilience using Bayesian networks: A case study of inland waterway ports. *Computers & Industrial Engineering*, *93*, 252–266. https://doi.org/10.1016/j.cie.2016.01.007

Hosseini, S., & Sarder, M. D. (2019). Development of a Bayesian network model for optimal site selection of electric vehicle charging station. *International Journal of Electrical Power & Energy Systems*, *105*, 110–122. https://doi.org/10.1016/j.ijepes.2018.08.011

Hosseini, S., Al Khaled, A., & Sarder, M. D. (2016). A general framework for assessing system resilience using Bayesian networks: A case study of sulfuric acid manufacturer. *Journal of Manufacturing Systems,* 41, 211–227. https://doi.org/10.1016/j.jmsy.2016.09.006

Johansen, C., & Tien, I. (2018). Probabilistic multi-scale modeling of interdependencies between critical infrastructure systems for resilience. *Sustainable and Resilient Infrastructure*, *3*(1), 1–15. https://doi.org/10.1080/23789689.2017.1345

Lawrence, J.-M., Ibne Hossain, N. U., Jaradat, R., & Hamilton, M. (2020). Leveraging a Bayesian network approach to model and analyze supplier vulnerability to severe weather risk: A case study of the U.S. pharmaceutical supply chain following Hurricane Maria. *International Journal of Disaster Risk Reduction, 49,* 101607. https://doi.org/10.1016/j.ijdrr.2020.101607

Marino, C., Marufuzzaman, M., Hu, M., & Sarder, M. D. (2018). Developing a CCHP-microgrid operation decision model under uncertainty. *Computers and Industrial Engineering, 115,* 354–367. https://doi.org/10.1016/j.cie.2017.11.021

Marino, C., Quddus, M. A., Marufuzzaman, M., Cowan, M., & Bednar, A. E. (2018). A chance-constrained two-stage stochastic programming model for reliable microgrid operations under power demand uncertainty. *Sustainable Energy, Grids and Networks*, *13*, 66–77. https://doi.org/10.1016/j.segan.2017.12.007

Marufuzzaman, M., & Eksioglu, S. D. (2017). Managing congestion in supply chains via dynamic freight routing: An application in the biomass supply chain. Transportation Research Part E: Logistics and Transportation Review, 99, 54–76. https://doi.org/10.1016/j.tre.2017.01.005

Marufuzzaman, M., Eksioglu, S. D., Li, X., & Wang, J. (2014). Analyzing the impact of intermodal-related risk to the design and management of biofuel supply chain. *Transportation Research Part E: Logistics and Transportation Review, 69*, 122–145. https://doi.org/10.1016/j.tre.2014.06.008

`Morais, C, Moura, R., Beer, M., & Patelli, E. (2018). Attempt to predict human error probability in different industry sectors using data from major accidents and Bayesian networks. *Probabilistic Safety Assessment and Management PSAM* (Vol. 14). https://www.researchgate.net/publication/328513274

Naderipour, A., Abdul-Malek, Z., Nowdeh, S. A., Ramachandaramurthy, V. K., Kalam, A., & Guerrero, J. M. (2020). Optimal allocation for combined heat and power system with respect to maximum allowable capacity for reduced losses and improved voltage profile and reliability of microgrids considering loading condition. *Energy*, *196*, 117124. https://doi.org/10.1016/j.energy.2020.117124

National Renewable Energy Laboratory, NREL. *The Biofuels Atlas.* Available from: https://maps.nrel.gov/biomass/?aL=QCty_y%255Bv%255D%3Dt&bL=clight&cE=0&lR=0&mC=40.21244%2C-91.625976&zL=4

National Weather Service Jackson Tornado database. Available from: http://midsouthtornadoes.msstate.edu/index.php?cw=jan

Quddus, M. A., Ibne Hossain, N. U., Mohammad, M., Jaradat, R. M., & Roni, M. S. (2017). Sustainable network design for multi-purpose pellet processing depots under biomass supply uncertainty. *Computers & Industrial Engineering*, *110*, 462–483. https://doi.org/10.1016/j.cie.2017.06.001

Stephenson, T. (2000). An introduction to Bayesian network theory and usage. *Idiap Research Report*, 31. http://ftp.idiap.ch/pub/reports/2000/rr00-03.pdf

U.S. Department of Energy. (2015). *United States Electricity Industry Primer*. Available from: https://www.energy.gov/sites/prod/files/2015/12/f28/united-states-electricity-industry-primer.pdf

U.S. Energy Information Administration (EIA) .(2020). Independent Statistics and Analysis. *U.S. customers experienced an average of nearly six hours of power interruptions in 2018* - Today in Energy - U.S. Energy Information Administration (EIA). Available from: https://www.eia.gov/todayinenergy/detail.php?id=43915#

Yu, D. C., Nguyen, T. C., & Haddawy, P. (1999). Bayesian network model for reliability assessment of power systems. *IEEE Transactions on Power Systems*, *14*(2), 426–432. https://doi.org/10.1109/59.761860

Zhang, J., Cho, H., & Knizley, A. (2016). Evaluation of financial incentives for combined heat and power (CHP) systems in U.S. regions. *Renewable and Sustainable Energy Reviews*, *59*, 738–762. https://doi.org/10.1016/j.rser.2016.0