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Assessing the Sensitivity of Bioenergy Parks to Capacity Disruptions using Monte Carlo Simulation

Michael Francis D. Benjamin*[,a], Raymond R. Tan[b], Luis F. Razon[b]

[a]Research Center for the Natural and Applied Sciences, University of Santo Tomas, España Blvd., 1015 Manila, Philippines
[b]Chemical Engineering Department, De La Salle University, 2401 Taft Avenue, 0922 Manila, Philippines
mdbenjamin@ust.edu.ph

Bioenergy parks are low carbon and production-efficient integrated networks, but are inherently vulnerable to cascading failures due to capacity disruptions (i.e. reduction in production levels). The reduction in production levels may be attributed to climate change-induced disruptions such as drought that results in lower supply of biofuel feedstocks. The extent of damage within a bioenergy park is dependent on network topology as well as magnitude of disruption. Thus, it is imperative for such systems to be designed properly in order to tolerate multiple disruption scenarios. Although individual bioenergy plants are designed to have minimum partial load or maximum rated capacities, such safety factor maybe trivial given that the effect of perturbations in highly integrated networks are either dampened or amplified. Thus, it is important to assess the sensitivity of a bioenergy park to fluctuations in the production levels of component plants. In this work, a Monte Carlo simulation approach is proposed to assess the vulnerability of bioenergy parks to variable capacity disruptions. Results show that the reliability of the final output is dependent on the component plant's connectivity within the network and highly-connected bioenergy plants results in high probability of failure. A case study on determining the robustness of the given network configuration is used to illustrate the methodology.

1. Introduction

Bioenergy parks are biomass processing complex that achieve sustainability through the concept industrial symbiosis (IS). Through IS, each bioenergy plant is integrated to other components within the network via material and energy exchanges (Chertow, 2000). Exchanges can be in the form of product and by-product synergies or by using common utilities such as electricity (Martin and Eklund, 2011). The concept of IS is already implemented at different scales such as in industrial complexes and regional levels. This system approach is already proven to be more efficient and incurs lower carbon footprint compared to stand-alone production plants. However, due to the interconnectivity of plants in a bioenergy park, such networks are inherently vulnerable to the cascading effect of capacity disruptions (Benjamin et al., 2015a). Capacity disruption usually happen when one plant becomes partially inoperable due to reduction in production level, in such case, the failure cascades or "ripples" through the entire network, causing the breakdown of other components. This disruption may cause certain plants to operate below its minimum rated capacity and eventually shut down due to economical considerations. It is important to include risk analysis in designing sustainable bioenergy systems such as a bioenergy parks.
Risk analysis requires qualitative and quantitative methods in determining what can go wrong (e.g., disruption scenario), estimating its likelihood, and measuring the extent of consequences (or vulnerability) of such event in a given system (Kaplan and Garrick, 1981). For bioenergy systems, the potential risk areas include the supply of biofuel feedstocks, plant or production facilities, and volatility of market prices of raw materials and products (Langholtz et al., 2014). In this work, we primarily focused on the reduction of feedstock supply for bioenergy production due to its direct link with climate change. The study of Langholtz et al. (2014) showed that bioenergy production is greatly affected by climate change-induced events, since the raw materials are mostly derived from agricultural sources. These disruptive events include droughts, extreme weather patterns (e.g. strong winds), and rising temperature levels that may damage agricultural crops in general. It is reported in the work of Bandara and Cai (2014) that agricultural productivity decreases by 8 % for every 1 °C increase in temperature.

The decline in biomass feedstocks will result in reduction in the bioenergy plants' production level and thus affecting the entire operation of bioenergy complexes or supply chains. It is therefore necessary to develop systematic methods to analyze the vulnerability of the bioenergy parks against an array of climate change-induced disruptions.

There are limited studies that focus on analyzing disruptions in bioenergy parks. Zhu and Ruth (2013) used a network model to simulate disruptions (i.e., removal of network components) using real case studies of industrial ecosystems. Their study focused on the effects of inter-plant connectivity and dependency to the overall resilience of the IS network. Chopra and Khanna (2014) used network indices (e.g., centrality index) to study the evolution of an IS network in describing its resilience. The works of Benjamin et al. (2015a; 2015b) focused on developing risk and resilience frameworks using input-output (I-O) analysis. These I-O models are important in designing sustainable bioenergy parks against anticipated capacity disruptions. A P-graph approach was recently developed by Tan et al. (2016) in order to optimally address a "crisis mode" or capacity disturbance in a bioenergy complex. However, the latter approach may not be able to capture the extent of vulnerability due to the deterministic nature of the approach.

Monte Carlo simulation is a method that can assess the sensitivity of a system's output by drawing its input in a predetermined probability distribution. This approach uses iterative methods in its numerical procedure to be able to generate sufficient data for statistical analysis. This method is used in reliability analysis of critical infrastructures (Johansson et al., 2013) and other engineered systems (Maheri, 2014). It is also used to determine the system's probability to function normally within specified limits (i.e., reliability), providing insights on vulnerability or robustness. Robustness is the ability to resist fluctuations or disruptions of a system and the inverse of vulnerability (Haimes et al., 2002). To date, Monte Carlo simulation has not been applied to determine the sensitivity of component plants within a bioenergy park against an array of disruptions. This approach offers additional insights regarding the vulnerability of a particular bioenergy park configuration and thus be able to guide design engineers in developing a more sustainable system. In this work, Monte Carlo simulation is used to assess the vulnerability of bioenergy parks to variable capacity disruptions due to reduction in biomass feedstocks. The rest of this paper is organized as follows. Section 2 gives the formal problem statement and Section 3 provides the methodological framework for the Monte Carlo simulation. A bioenergy park case study is then presented in Section 4 to demonstrate the approach. Finally, Section 5 gives the conclusions and future research works.

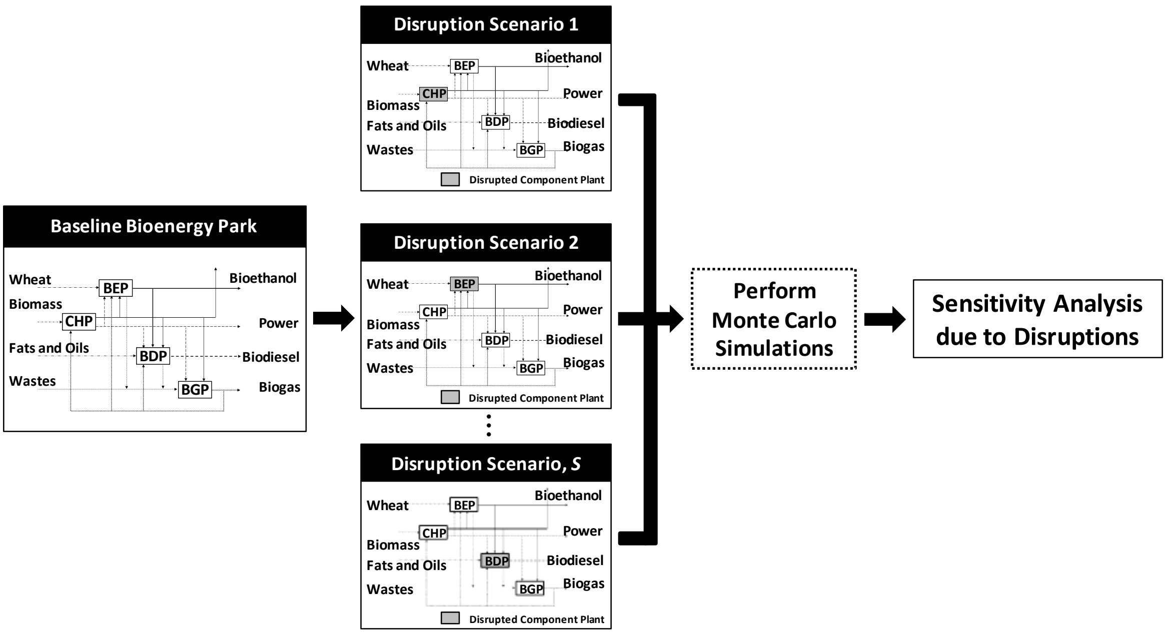

Figure 1: General framework for sensitivity analysis of bioenergy park due to disruption.

2. Problem Statement

Assume a baseline network configuration (i.e., input-output flows, production levels, net output) of a bioenergy park. For each scenario (e.g., Scenario 1, CHP plant), a particular component plant is disrupted due to reduction in feedstock supplies. This disruption is assumed to affect the production level of the bioenergy plant resulting in decrease in net output of its corresponding product stream (i.e., power). The method is adapted from the Criticality Analysis developed by Benjamin et al. (2015a). A Monte Carlo simulation is then used to determine the effect of disruption variations in plant capacities and final output of the bioenergy park. The scenarios will then be compared to determine the most sensitive component or product stream due to fluctuations or multiple disruptions. Figure 1 shows the general framework for assessing the sensitivity of the bioenergy park to capacity disruptions.

3. Methodology

Key material or energy balances are used to describe each bioenergy plant in the network. The entire bioenergy park is then modelled using I-O analysis and its matrix form is shown in Eq(1); where $\mathbf{A}$ is the process matrix that contains the ratios of mass or energy balances, $\mathbf{x}$ is the bioenergy plant capacity vector (i.e., production level), and $\mathbf{y}$ is the final output vector. A model developed for exogenously-defined capacity of component plants and exogenous final output of a bioenergy park is used. This supply-side disruption approach is based on the method developed by Benjamin et al. (2015a). We then assume single-plant disruption and its consequence is quantified in terms of the reduction in the affected product stream of the bioenergy park. The reduced final output stream, $\mathbf{y}''$, is solved using Eq(2). The detailed description of the model is found in Benjamin et al. (2015a). This approach quantifies the downstream effect of disruption via the change in the net output of each bioenergy plant. The fractional change in the net output, relative to the baseline state, is then computed. Variation in the magnitude of disruption per scenario is simulated using Monte Carlo. Using this method, the resulting statistical properties of a system's output based from a given probability distribution of its inputs will then be determined. In this work, the properties of the final output of the bioenergy parks are analyzed given fluctuations (i.e., multiple disruptions) in the production levels of a particular component plant. Statistical mean and standard deviation will be computed after a predetermined number of iterations. The changes in the final output will then be displayed using range bar graphs to determine the sensitivity to disruption. Reliability (or probability of failure) will then be calculated based on predefined system safety factors. Figure 2 shows the general procedure for Monte Carlo simulation.

$$\mathbf{A}\,\mathbf{x} = \mathbf{y}\,, \tag{1}$$

$$\begin{bmatrix} \mathbf{0} & \mathbf{A}' \\ -\mathbf{I} & \mathbf{A}'' \end{bmatrix} \begin{bmatrix} \mathbf{y}'' \\ \mathbf{x}' \end{bmatrix} = \begin{bmatrix} \mathbf{B}' & \mathbf{I} \\ \mathbf{B}'' & \mathbf{0} \end{bmatrix} \begin{bmatrix} \mathbf{x}'' \\ \mathbf{y}' \end{bmatrix}, \tag{2}$$

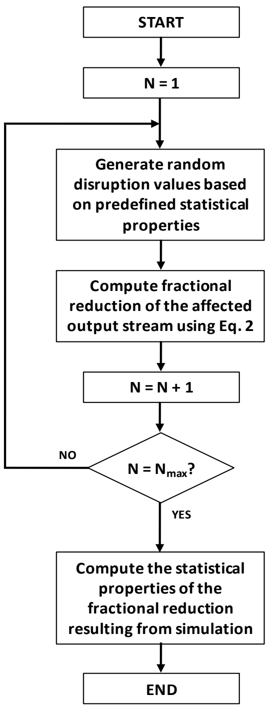

Figure 2: General procedure for Monte Carlo simulation (adapted from Tan et al., 2007).

4. Case Study

Monte Carlo simulation was used to determine the vulnerability of bioenergy parks using the network described in Martin and Eklund (2011) and modified by Benjamin et al. (2015a). Figure 3 shows the baseline state of the bioenergy park; these include flowrates of raw materials, required production capacities, and net output of products. The component plants in the network consist of a combined heat and power plant (CHP) that supplies electricity and steam, bioethanol plant (BEP), biodiesel plant (BDP), and a biogas plant (BGP). The feasible operating range based on the baseline state and other design data are given in Table 1. This indicates that the CHP can operate between 95 – 110 % of the baseline capacity of 30,881 kW. In this study, the disruptions are assumed to be variable and follow a normal probability distribution with a mean value of 10 % and standard deviation of 5 %. The net output is also assumed to allow flexibility within the 80 – 120 % range. Operational flexibility allows a system to function in pseudo steady-state within specified limits (Swaney and Grossmann, 1985). Values that are outside the operating range are assumed to cause a "failure of design" in the system and the number of its occurrence will determine system reliability. Failure of design is defined in this work as the state wherein the simulated value is beyond the feasible operating range. This definition is similar to the one proposed by Hohmann (1971) in performing robustness analysis for heat exchange networks.
A spreadsheet program was used to perform the Monte Carlo simulation using 1,000 iterations. The sensitivity of the production capacities of the bioenergy plants as well as the final output to varying disruptions was determined. Figure 4 shows the range of the values of the reduction in final output for each scenario from the Monte Carlo simulation. Variation in the final output is an indicator of the sensitivity of a particular component plant to disruption and indicative of its vulnerability to an array of probabilistic disruption. From the results, it can be seen that the most sensitive plant is the BGP which is also the most vital plant based from the Criticality Analysis study of Benjamin et al. (2015). The disruption of the BGP plant caused a higher reduction in its net output (i.e., biogas) compared to other bioenergy plants. It is therefore important to perform operational adjustments to reduce fluctuations in the final output through system redundancy.

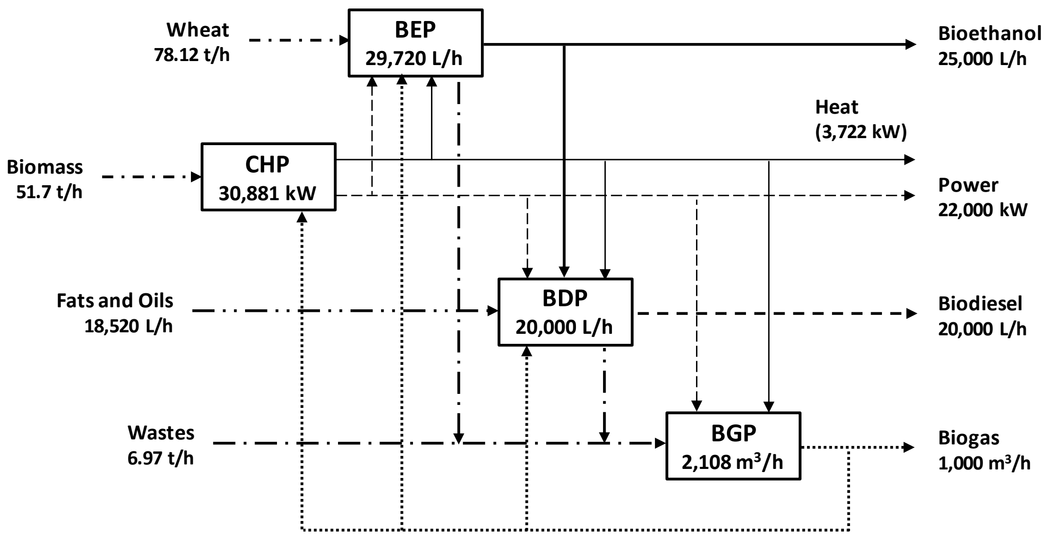

Figure 3: Baseline state of the bioenergy park (adapted from Benjamin et al., 2015a).

Table 1: Design data for the bioenergy park

Scenario	Disrupted component plant	Design production capacity	Feasible operating range (%)	Mean capacity disruption	Capacity disruption standard deviation	Distribution
Scenario 1	CHP	30,881 kW	95 – 110	0.1	0.05	Normal
Scenario 2	BEP	29,720 L/h	95 – 120	0.1	0.05	Normal
Scenario 3	BDP	20,000 L/h	90 – 112	0.1	0.05	Normal
Scenario 4	BGP	2,108 m^3/h	92 – 105	0.1	0.05	Normal

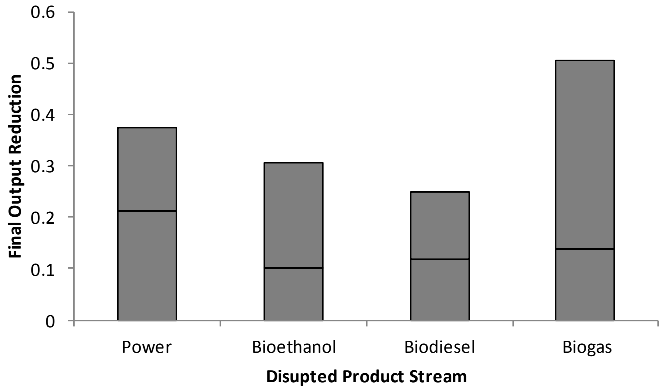

Figure 4: Reduction in final output of the bioenergy park.

The summary of simulation iterations are presented in Tables 2 and 3. Table 2 shows the mean value and the standard deviation of the production levels of the disrupted bioenergy plants. It can be seen from Scenario 1 that on the average, BGP is just producing 2,017 m^3/h of biogas with a standard deviation of 44 m^3/h. Other components with zero standard deviation suggest that the plant is operating at the mean value (i.e., the baseline value in this case) and is not affected by the given disruption. It can also be seen in the table that for Scenario 1 the probability of BGP's capacity to be less than 92 % (i.e., 1,939 m^3/h) is 3.5 %. The probability of failure for both BEP and BDP is practically zero, which shows that these plants operate at the given feasible range and are unaffected by the disruption of the CHP. For other scenarios that have negligible failure probabilities for component plants, this shows their ability to absorb fluctuations without operating below the design limit.

Table 2: Summary of results for the bioenergy park component plants

Scenario	Component plant	Production capacity		
		Mean value	Standard deviation	Failure probability (%)
1	BEP (L/h)	29,720	0	0
	BDP (L/h)	20,000	0	0
	BGP (m^3/h)	2,017	44	3.5
2	CHP (kW)	30,082	381	3.0
	BDP (L/h)	20,000	0	0
	BGP (m^3/h)	2,073	17	0
3	CHP (kW)	30,723	76	0
	BEP (L/h)	29,239	231	0
	BGP (m^3/h)	2,095	7	0
4	CHP (kW)	30,788	44	0
	BEP (L/h)	29,720	0	0
	BDP (L/h)	20,000	0	0

Table 3: Summary of results for the bioenergy park final output

Scenario	Disrupted product stream	Final output		
		Mean value	Standard deviation	Failure probability (%)
1	Power (kW)	18,987	1,263	17.2
2	Bioethanol (L/h)	22,071	1,265	8.9
3	Biodiesel (L/h)	17,977	859	2.0
4	Biogas (m^3/h)	787	76	54.4

Table 3 on the other hand presents the mean and standard value of the disrupted final output per scenario. For Scenario 1, the mean net output of power is 18,987 kW with a standard deviation of 1,263 kW. Failure of design probabilities are also presented in Table 3. These values can be compared or ranked to determine relative reliabilities of each component plant. Results show that the biogas output has the highest probability of failure compared to other plants in the network. This suggests that around one-half of the time, the net output of the

BGP is below 80 % (i.e., 800 m^3/h) of the baseline value. System reliability can be increased by retrofitting existing plants in bioenergy parks in order to increase the capacity of bottleneck components.

5. Conclusions

A Monte Carlo simulation-based method for determining the vulnerability of component plants in a bioenergy park was developed in this work. This approach is important in identifying bioenergy plants and product streams that are sensitive to fluctuations in production capacities brought about by climate change-induced events. The insights from this work are useful for design engineers in developing robust and reliable networks capable of tolerating an array of probabilistic disruptions. In this work, the most disruption-sensitive bioenergy plant is the highly-connected component in the network (i.e., biogas plant) which results in lower reliability in producing its final output (i.e., biogas). Future works will focus on using Monte Carlo simulation in assessing the effect of uncertainties in the final output and modeling multiple-plant disruption scenarios. This work can also be extended in analyzing the robustness of alternate bioenergy park designs for determining optimal network configurations in conjunction with the P-graph method (Aviso et al., 2015).

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