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Analyzing the Disruption Resilience of Microalgal Multi-functional Bioenergy Systems using Dynamic Inoperability Input-output Modeling

Michael F. Benjamin*[a], Aristotle Ubando[b], Luis Razon[a], Raymond R. Tan[a]

[a]Chemical Engineering Department, De La Salle University, 2401 Taft Avenue, 0922 Manila, Philippines
[b]Mechanical Engineering Department, De La Salle University, 2401 Taft Avenue, 0922 Manila, Philippines
michael_benjamin@dlsu.edu.ph

Bioenergy parks are low-carbon industrial symbiosis (IS) networks that are also characterized as having a higher resource efficiency and economic sustainability compared to stand-alone bioenergy plants. A microalgal multi-functional bioenergy system (MMBS) is an example of such network, which is specifically developed for the sustainability of algal biofuels. However, such highly integrated energy system is inherently vulnerable to capacity disruptions resulting in a less resilient network. The strong interdependence between component plants in a bioenergy park decreases system resilience due to cascading failure effect. The consequence of such disruption is even greater if the critical components are damaged. Resilience is defined in this work as the ability of an energy system to withstand a disruption and be able to recover to normal operating conditions. Most risk analysis focus on the vulnerability or robustness (i.e., static resilience) of bioenergy parks and lack significant discussions on the recovery rates aspect (i.e., dynamic resilience). In this work, a disruption resilience framework is developed to analyze the resilience of bioenergy parks against an array of capacity disruption scenarios. This study is primarily focused on the effect of single-plant disruption scenarios. The proposed framework is derived from the concepts of dynamic inoperability input-output modelling (DIIM) used in economic systems. The method shows that the resilience of the bioenergy park is influenced by the recovery time of bioenergy plants and their degree of connectivity within the network. The insights from this work can be used for planning and developing more disruption-resilient bioenergy parks. An MMBS case study is presented to demonstrate the applicability of the resilience framework.

1. Introduction

A bioenergy park is an industrial symbiosis (IS) network that is characterized by having lower carbon emissions (Ubando et al., 2014), higher resource efficiency (Aviso, 2014), and greater economic sustainability (Ng et al., 2015) compared to stand-alone bioenergy plants. A bioenergy park is developed through material and energy exchanges between existing bioenergy plants in order to maximize the use of products, by-products, and production wastes. An example of such bioenergy park is a microalgal multi-functional bioenergy system (MMBS) (Ubando et al., 2014), which is developed to achieve sustainability in the production of algal biofuels. This system is an array of interconnected facilities consisting of integrated microalgal cultivation to biodiesel plant and auxiliary bioenergy production plants. Bioenergy parks are highly integrated and highly interdependent energy systems; however, these inherent system properties increase the risk of propagating failure in case of component disruptions. Cascading failure occurs when a disruption in one component causes the failure of one or more components in a tightly coupled network such as an MMBS. A study by Zhu and Ruth (2013) shows that IS networks in general are less resilient when there is a high interdependency between components and the disruption originates from a highly connected plant. Benjamin et al. (2014) even demonstrated that the criticality (i.e., consequences of disruption) of components plants in a bioenergy park is greater if the failure originates from bioenergy plants with a high degree of connectivity within the network.

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Resilience is an emergent property that is needed to improve the sustainability of IS networks (Chopra and Khanna, 2014) and other engineered systems (Salzano et al., 2014). The definition of resilience, in this work, is similar to the one proposed by Haimes (2009) using a systems-based approach. It is the ability of the system to withstand a major disruption within acceptable degradation parameters and to recover within an acceptable time (including cost and risk). The resilience or recovery of disrupted component plants in a bioenergy park can be modeled using the dynamic inoperability input-output model (DIIM) initially developed for economic systems. DIIM originates from the concepts of input-output (I-O) analysis proposed by Leontief (1936) that accounts for linear interdependencies (i.e., monetary) of economic sectors. The I-O model was then adapted by Haimes and Jiang (2001) to introduce the concept of inoperability and later on by Santos and Haimes (2004) by developing the demand-reduction inoperability input-output model (IIM). The IIM framework was then extended to a dynamic model to account for resilience measures that considers recovery aspects (Lian and Haimes, 2006). Further modifications and applications of the dynamic model include the following: a recovery model to analyze the effect of natural disasters to workforce systems (Akhtar and Santos, 2013) and using a hybrid IIM – event tree model as a decision-making tool in aiding the recovery of interdependent economic sectors (Santos et al., 2014). However, to date, DIIM has not been applied to analyze the resilience of bioenergy parks.
In this work, a *disruption resilience framework* is proposed to analyze the recovery of bioenergy plants in an MMBS. This novel approach integrates the concepts of DIIM in understanding the resiliency of this bioenergy park against an array of disruption scenarios (i.e., single-plant disruptions). The proposed framework determines the effect of component plant criticality and interdependencies in the recovery time. This present work contributes in understanding disruption risks and recovery of component plants in a bioenergy park, which are underdeveloped research areas in IS networks. The rest of the article is organized as follows. A formal problem statement and methodology deriving the disruption resilience framework is presented in the next sections. An MMBS case study is then presented to demonstrate the applicability of the resilience framework. Lastly, conclusions and future works are presented towards the end of the paper.

2. Problem Statement

Assume than an MMBS is composed of *n* number of bioenergy plants. Each component plant is described by scale-invariant material or energy balance ratios. It is assumed that each bioenergy plant produces a main product stream. For a given *i-th* scenario, one particular component plant is disrupted. The method also assumes that the reduction in the capacity (i.e., baseline production level) of the bioenergy plant only affects its corresponding final output stream. A method developed by Benjamin et al. (2014) for determining the criticality of each component plant is then used. Finally, the recovery of disrupted bioenergy plants in the five scenarios will be determined and analyzed using DIIM. For each scenario, the bioenergy plant is assigned a recovery coefficient, k, and an initial inoperability, q. Figure 1 shows the summary for developing the disruption resilience framework.

3. Methodology

This section presents the disruption resilience framework developed for bioenergy parks. Each component plant in the bioenergy park is described using key mass and energy balances. The MMBS is then represented using a physical input-output model and the matrix form is given by Eq(1).

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

$\mathbf{A}$ is the *process matrix* that contains mass and energy balance coefficient ratios in the MMBS, $\mathbf{x}$ is the *component plant capacity vector, a*nd $\mathbf{y}$ is the *final output vector*. The criticality of each disrupted bioenergy plant is determined using the method developed by Benjamin et al. (2014). Criticality, c, is defined as the fractional change in the final output of the affected product streams relative to the baseline state. The recovery of the disrupted component plant in each scenario is then determined using the DIIM shown in Eq(2) (Lian and Haimes, 2006).

$$\mathbf{q}(t+1) = \mathbf{q}(t) + \mathbf{K}(\mathbf{A}^{*}\mathbf{q}(t) + \mathbf{c}^{*}(t) - \mathbf{q}(t)) \tag{2}$$

$\mathbf{q}$ is the *inoperability vector* or disruption vector of bioenergy plants, a risk metric ($0 \leqslant \mathbf{q} \leqslant 1$) that describes the inability to maintain the desired production levels at a specified time period (t). An inoperability value of 0 means that the bioenergy plant is operating at the desired production level and a value of 1 means the plant is completely disrupted. $\mathbf{K}$ is the *recovery matrix* (i.e., diagonal matrix) that describes the ability of the bioenergy park to recover (in a given time period) from an initial disruption level to a completely operable state (**q** = 0). The diagonal elements (k_{nn}) in the matrix represent the recovery speed of each bioenergy plant to the disruption including other inherent characteristics. $\mathbf{A}^*$ is the *interdependency matrix* (i.e., normalized square matrix) that represents the degree of coupling of the component plants. $\mathbf{c}^*$ is the *perturbation vector* that contains final output-side disruptions that may occur after the initial disruption. Please see the works of Santos and Haimes (2004) – on the demand reduction and Lian and Haimes (2006) – on the risk management, for a complete derivation of Eq(2).

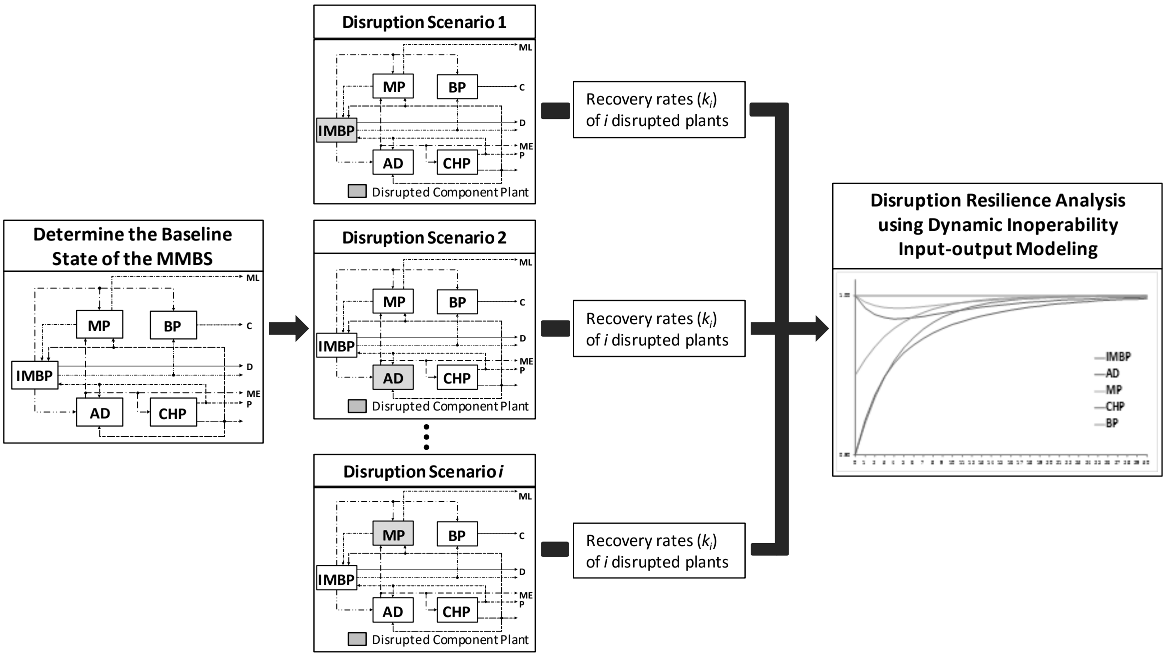

Figure 1: Disruption resilience analytical framework

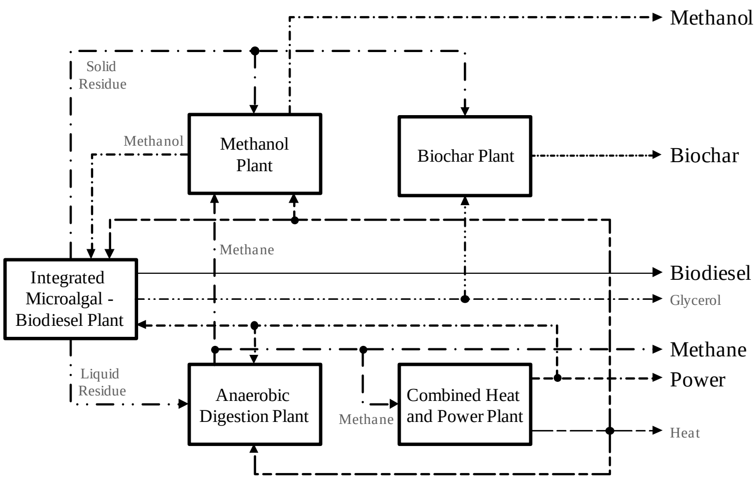

Figure 2: Microalgal multi-functional bioenergy system flow diagram (adapted from Ubando et al., 2014)

4. Case study: Microalgal multi-functional bioenergy system

This MMBS case study is adapted from the bioenergy park described by Ubando et al. (2014). The MMBS shown in Figure 2 contains the following component plants: integrated microalgal to biodiesel plant (IMBP), methanol plant (MP), biochar plant (BP), anaerobic digestion plant (AD), and combined heat and power plant (CHP). These bioenergy plants are designed to produce the following main product streams: biodiesel (D), methanol (ML), biochar (C), methane (ME), and power (P) respectively. It is assumed that each *nth* component plant (e.g., IMBP) produces a main product stream (e.g., biodiesel) as its output. The

MMBS process matrix $\mathbf{A}$ consists of the first five data rows and first five data columns of Table 1. The final output vector $\mathbf{y}$ consists of the first five data rows of the last column of the same table. Each column in the process matrix $\mathbf{A}$ is considered a process vector wherein key scale-invariant mass and energy balance ratios in each bioenergy plant are given. The baseline capacities (i.e., desired production levels) of the bioenergy plants are solved using Eq(1) and presented in Table 2.

Table 1: Process data for the baseline state of the MMBS (adapted from Ubando et al., 2014)

Product stream	IMBP	AD	MP	CHP	BP	Final output
Biodiesel, kg/s	1	0	0	0	0	19
Methane, kg/s	0	1	–0.43	–0.09	0	80
Methanol, kg/s	–0.12	0	1	0	0	10
Power, MW	–17.2	–2.82	0	1	0	5,000
Biochar, kg/s	0	0	0	0	1	20

Table 2: Baseline production levels of the MMBS

Bioenergy plant	IMBP, kg/s	AD, kg/s	MP, kg/s	CHP, MW	BP, kg/s
Plant capacity	19	756.75	12.28	7,460.86	20

After determining the baseline production levels of the bioenergy plants, the criticality of each component plant is solved using the method developed by Benjamin et al. (2014). A 5 % reduction in production level is assumed for computing the consequence of each single-plant disruption scenario. The scenarios are then ranked based on the criticality (i.e., net output change based on disruption) as shown in Table 3. It can be seen in the table that the most critical bioenergy plant in the MMBS is the AD. This means that the disruption of this bioenergy plant causes greater damage to the network compared to other component plants. The next critical bioenergy plant is the MP, then CHP, IMBP, and BP. In general, the criticality is greatly influenced by the components' degree of connectivity within the network. Those component plants without feedback loops are considered to be least damaging in the bioenergy park as shown in Table 3. Risk management measures should be in place to protect critical infrastructures in the network, thus avoiding highly damaging events.

Table 3: Criticality of bioenergy plants

Scenario	Disrupted component plant	Criticality, c	Rank
Scenario 1	IMBP	0.010	4
Scenario 2	AD	0.071	1
Scenario 3	MP	0.012	2
Scenario 4	CHP	0.011	3
Scenario 5	BP	0.010	4

After analyzing the effect of single-plant disruptions in the MMBS, DIIM is used to study the recovery of the component plants and the resilience of the bioenergy park. For a given *ith* scenario, each bioenergy plant is assigned a recovery coefficient and an initial inoperability. For illustration purposes, it is assumed that the inoperability of the disrupted component plant in all scenarios is 20 % (q = 0.2) or the production level is degraded to 80 % ($1 - q$). It is further assumed that the recovery coefficient for all bioenergy plants is 0.25 (k = 0.25) and the production levels will recover to baseline capacity (c^* = 0). In this work, the disruption resilience was measured in terms of the approximate time for the entire bioenergy park to recover to 99 % production level, similar to most DIIM studies.
Figures 3 to 7 shows the dynamic recovery of single-plant disruption scenarios in the MMBS. It can be seen that even though some component plants are not initially disrupted (e.g., in Figure 4), they become disrupted due to its interdependency with other bioenergy plants. This additional disruption due to interdependency affects the overall resilience of the MMBS. It can also be seen that faster full recovery is attained when the disrupted component plant (e.g., BP) is sparsely connected in the network or there are no internal requirements for their main product. It can be seen from these figures that it takes longer time to attain full recovery if the disruption originated from critical components (e.g., AD) of the bioenergy park. It terms of recovery time, it means that the bioenergy park is less resilient when the anaerobic digestion

plant becomes inoperable. This also affects the resilience cost (i.e., repair cost + production losses cost) as additional cost due to losses in production is increased as the time to full recovery lengthens.
In addition, although MP is the second most critical plant it has a relatively faster recovery time, this can be due to its low level of dependency to other components. According to Zhu and Ruth (2013), the disruption of connected plants such as the methanol plant will not affect network resiliency if the dependency is low. However, if the interdependency is high as seen from Figures 4 and 6, the recovery time is affected. It can be seen from Figure 6 that at many points during the repair of CHP, the inoperability of AD is greater than that of the initial disrupted component plant. To sum, the previous observations suggest that the resilience (or recovery time) of the bioenergy park depends both on the network connectivity and level of component interdependency. In this particular case study, it is shown that the bioenergy park is less resilient (i.e., longer recovery time needed) if the disrupted plants are highly connected and has high level of interdependency with other components within the network. Also, relatively longer recovery time is attained if the type of scenario has high disruption consequence (e.g., scenario 2).

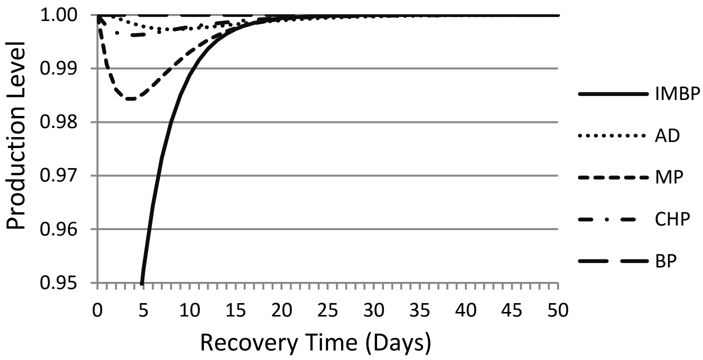

Figure 3: Dynamic recovery of disruption scenario 1 (IMBP)

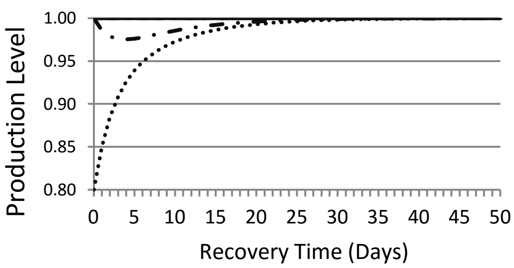

Figure 4: Dynamic recovery of scenario 2 (AD)

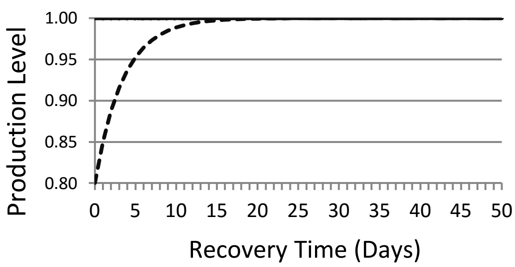

Figure 5: Dynamic recovery of scenario 3 (MP)

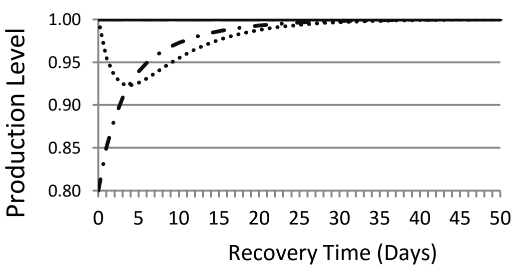

Figure 6: Dynamic recovery of scenario 4 (CHP)

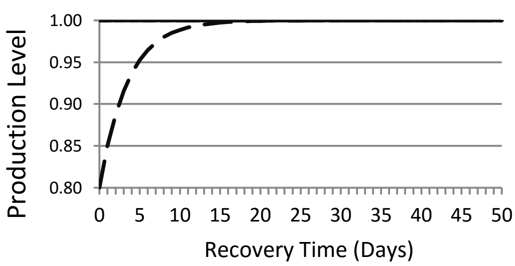

Figure 7: Dynamic recovery of scenario 5 (BP)

These results necessitate risk managers to create strategies and policies to mitigate the disruption consequence of critical components in the bioenergy park. At the same time, the repair or recovery time must be decreased in case the disruptions originate from these critical components. Aside from these, increased system resiliency can be addressed by implementing redundancy, increasing spare capacity, and adding multi-functionality (Chopra and Khanna, 2014). The disruption resilience framework proposed in this study is an initial step and contributes greatly in understanding the dynamic complexities present in IS networks, particularly in bioenergy parks.

5. Conclusions

A novel disruption resilience framework was developed in this work to analyze the recovery of component plants and understand the overall resilience of bioenergy parks. The concepts of DIIM are used to analyze the resiliency of an MMBS against single-plant disruption scenarios. The proposed framework demonstrated that the resilience of the MMBS is influenced by the recovery time of each bioenergy plant and interdependencies within the network. The present work contributes in understanding the relatively underdeveloped research area in IS networks, which are disruption risks and resiliency of bioenergy parks. Risk-based insights from this study can be used as inputs for planning and developing more disruption-resilient bioenergy parks. Future work will focus on estimating the recovery coefficients of the MMBS, since such value is influenced by specific physical characteristics and risk management policies.

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