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Probabilistic Multi-disruption Risk Analysis in Bioenergy Parks via Physical Input-Output Modeling

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ABSTRACT

Bioenergy parks are integrated energy systems developed based on material and energy synergies among bioenergy and auxiliary plants to increase efficiency and reduce carbon emissions. However, the resulting high interdependence between component units results to a vulnerable network upon capacity disruptions (i.e., plant inoperability). Inoperability of one or more plants within a bioenergy park results in a deviation from an initial network configuration because of failure propagation. The consequences of such disruptions depend upon which component units caused the failure. In this work, a probabilistic multi-disruption risk index is developed to measure the net output change of a bioenergy park based on exogenously-defined plant disruption scenarios. This network index is an important measure of the system's robustness to an array of probabilistic perturbation scenarios. Such risk-based information can be used for developing risk management measures to reduce network vulnerability through increasing system redundancy and diversity. A bioenergy park case study is presented to demonstrate the computation of the multi-disruption risk index.

KEYWORDS: Probabilistic risk analysis, bioenergy parks, physical input-output model, analytic hierarchy process, multi-disruption scenarios

1 INTRODUCTION

The creation of "bioenergy parks" offers the prospect of increased efficiency and reduced carbon emissions compared to stand-alone bioenergy plants. A bioenergy park is an industrial symbiosis (IS) network that is developed based on material (or energy) synergies (Martin and Eklund, 2011) and potential economic gains (Gonela and Zhang, 2014). Sustainability is achieved in IS networks through product, by-product, and utility exchanges among separate component plants by cooperating or collocating (Chertow, 2000). However, the resulting highly-integrated system and strong interdependency among component plants increases network vulnerability against plant capacity disruption (Chopra and Khanna, 2014). In this work, capacity disruption is defined as the reduction in the desired production levels of the bioenergy plants and is similar to the concept of sectoral inoperability used in economic systems (Santos and Haimes, 2004). Component plant disruptions in a bioenergy park may result in an overall decrease in economic and environmental gains of the network. The consequences of such disruption are demonstrated to be larger if the source of failure originates from critical component plants in the bioenergy park (Benjamin et al., 2014). This risk necessitates the need to develop a framework to quantify and analyze the consequences of plant disruptions within a bioenergy park.

The quantification of risks must be described by a well-defined risk metric (Johansen and Rausand, 2014). A simplified expression of risk is presented in Eq. (1) which is based on the summary of risk definitions by Veland and Aven (2013),

$$\mathrm{Risk} = \mathrm{P(A)} * \mathrm{C}, \tag{1}$$

where $\mathrm{P(A)}$ is the probability of an event A to occur and C is the corresponding consequence of that event, where it may be measured in terms of economic loss, environmental damage or loss of lives (Johansen and Rausand, 2014).

In this work, the probability term in the risk index will be determined using the pairwise comparison method used in the traditional analytic hierarchy process (AHP). AHP is a widely-used decision-making tool that incorporates both qualitative and quantitative factors (Saaty, 1977). AHP achieves systematic calculation of global priorities in complex problems, based on a structural decomposition strategy to allow for local pairwise comparisons (Ishizaka and Labib, 2011). On the other hand, the consequences or effect of plant disruptions in a bioenergy park can be modeled using input-output (IO) analysis. This approach was initially developed for modeling quantitative relationships between economic sectors (Leontief, 1936); however, its use has been extended in analyzing industrial complexes. IO analysis is a systematic method to quantify the relationship between the components of a complex system (Miller and Blair, 1985). IO and AHP-based approaches have not been explicitly used to develop a framework to quantify and analyze the risks resulting from plant capacity disruptions within bioenergy parks. This present work addresses this research gap and contributes knowledge in understanding the vulnerabilities present in IS networks.

In this work, a probabilistic *multi-disruption risk index* is proposed to quantify the consequence of plant capacity disruptions within a bioenergy park. It is defined as an aggregated and weighted net output change of the bioenergy park based on multiple, mutually exclusive disruptions scenarios. This network index is an important measure of the system's robustness to an array of probabilistic capacity perturbation scenarios.

2 METHODOLOGY

This section presents the method to derive the multi-disruption risk index for bioenergy parks. Each bioenergy plant is described using key mass or energy balances and this network can be expressed using a physical input-output model via its matrix form shown in Eq. (2). $\mathbf{A}$ is the *process matrix* that contains coefficient ratios of mass or energy balances in the bioenergy park, $\mathbf{x}$ is the *bioenergy plant capacity vector*, and $\mathbf{y}$ is the *final output vector*. A model developed for exogenously-defined capacity of component plants as well as exogenous final outputs of a network is then used. This model is based on the method developed for industrial networks (Khanna and Bakshi, 2009). Mathematical rearrangement of Eq. (2) yields Eq. (3).

For an $n \times n$ matrix (i.e., a bioenergy park with n component plants), k is the set of exogenously-defined final output streams (y_1, y_2,…, y_k), and the remaining $(n - k)$ set is the exogenously-defined capacity vector that contains the disrupted capacity of component plants (x_{k+1}, x_{k+2},…, x_n). $\mathbf{A}'$ is the $k \times k$ matrix containing the elements from the k rows and k columns in matrix $\mathbf{A}$. $\mathbf{A}''$ is the $(n - k) \times k$ matrix containing the elements from the $(n - k)$ rows and k columns in matrix $\mathbf{A}$. $\mathbf{B}'$ is the $k \times (n - k)$ matrix containing the elements from the k rows and $(n - k)$ columns in matrix $(-\mathbf{A})$. $\mathbf{B}''$ is the $(n - k) \times (n - k)$ matrix containing the elements from the $(n - k)$ rows and $(n - k)$ columns in matrix $(-\mathbf{A})$.

Meanwhile, $\mathbf{x}'$ is the k-element column vector containing x_1 to x_k, which are the endogenous capacity of the component plants and $\mathbf{x}''$ is the $(n - k)$ element column vector containing x_{k+1} to x_n, which are the component plants with specified disrupted capacities. $\mathbf{y}'$ is the *k*-element column vector containing elements y_1 to y_k which are the exogenously-defined final outputs. Lastly, $\mathbf{y}''$ is the *(n – k)* element column vector containing elements y_{k+1} to y_n, which are the reduced final output streams.

The probabilities are determined using an AHP-based approach by pairwise comparison of all scenarios. In this work, hypothetical expert judgment values were used to weigh the relative probability of the disruption scenario to happen. Table 1 shows a modified AHP scale based on the likelihood of a given disruption scenario to occur over another.

Table 1 Modified 1-9 AHP measurement scale based on relative probability of occurrence

Intensity of probability	Definition
1	Equally probable
3	Moderately more probable
5	Highly more probable
7	Very highly more probable
9	Extremely more probable
2, 4, 6, and 8	Intermediate values between two adjacent intensities

To determine the consequence of plant disruptions in a bioenergy park, let us assume that for a given *ith* scenario, *j* bioenergy plants are reduced in capacity by *h%*. The reduced final output streams, $\mathbf{y}''$, per scenario are solved using Eq. (3). To compute for the fractional change in the net output of the affected product streams, we define Eq. (4). $\mathbf{c}$ is the *criticality column vector* containing the fractional change of the reduced output streams relative to the baseline state. $\mathbf{y}^*$ is the column vector containing the baseline value of the affected output streams, $\mathbf{y}''$ is the column vector containing the reduced final output of the product streams. Lastly, $\widehat{\mathbf{Y}}^*$ is a diagonal matrix containing the baseline value of the affected output streams. To compute for the average fractional change in the net output of the bioenergy park, we define Eq. (5). $\mathbf{d}$ is the *disruption consequence column vector* containing the mean fractional change in the final output of the bioenergy park in all scenarios. The risk index per scenario is given by Eq. (6).

$$\mathbf{A}\,\mathbf{x} = \mathbf{y} \tag{2}$$

$$\begin{bmatrix} \mathbf{0} & \mathbf{A}' \\ -\mathbf{I} & \mathbf{A}'' \end{bmatrix}\begin{bmatrix} \mathbf{y}'' \\ \mathbf{x}' \end{bmatrix} = \begin{bmatrix} \mathbf{B}' & \mathbf{I} \\ \mathbf{B}'' & \mathbf{0} \end{bmatrix}\begin{bmatrix} \mathbf{x}'' \\ \mathbf{y}' \end{bmatrix} \tag{3}$$

$$\mathbf{c} = \left(\mathbf{y}^* - \mathbf{y}''\right)\widehat{\mathbf{Y}}^{*-\mathbf{1}} = \left(c_j\right) \tag{4}$$

$$\mathbf{d} = (d_i) = (\textstyle\sum_{j=1}^{j} c_j)n^{-1} = (\sum(c_1 + c_2 + \cdots c_j))/n \tag{5}$$

$$R_i = p_i d_i \tag{6}$$

$$R_M = \textstyle\sum_{i=1}^{i} p_i d_i = \sum(p_1 d_1 + p_2 d_2 + \cdots p_i d_i) = \sum(R_1 + R_2 + \cdots R_i) \tag{7}$$

Finally, the multi-disruption risk index for the bioenergy park is shown in Eq. (7). R_M is the *multi-disruption risk index*, p_i is the *probability* that the *ith* disruption scenario occurs resulting to a corresponding *consequence*, d_i. This risk index measures the aggregate change in the net output of the bioenergy network under multiple probabilistic disruption scenarios.

3 CASE STUDY: BIOENERGY PARK

This bioenergy park case study is originally adapted from the system described by Martin and Eklund (2011), using the additional assumptions described in Benjamin et al. (2014). The hypothetical IS network shown in Figure 1 contains the following component plants: combined heat and power plant (CHP), bioethanol plant (BEP), biodiesel plant (BDP), and a biogas plant (BGP). These bioenergy plants are designed to produce the following main product streams: power (P), bioethanol (E), biodiesel (D), and biogas (G) respectively. It is assumed that each *nth* component plant (e.g., bioethanol plant) produces a main product stream (e.g., bioethanol) as its output. Process matrix **A** is constructed using the first four data rows and first four data columns of Table 2. The final output vector **y** contains the first four data rows of the last column. Each column in matrix **A** is considered a process vector wherein scale-invariant ratios of key mass or energy balances in each bioenergy plant are given. The baseline capacities of the bioenergy plants, including input streams, are solved using Eq. (2).

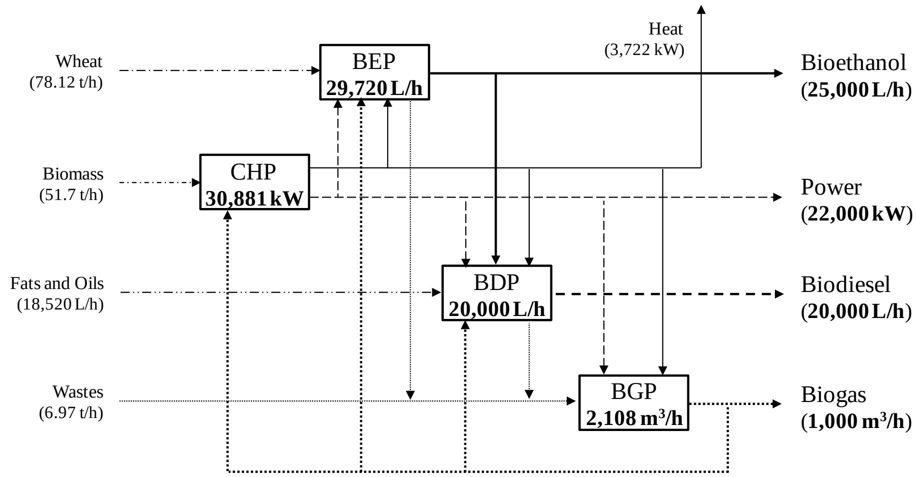

Figure 1: Bioenergy park baseline input and output flow diagram

Table 2 Process data for the baseline state of the bioenergy park (adapted from Benjamin et al., 2014)

Stream	CHP Plant	BEP	BDP	BGP	Final Output
Power, kW	1	–0.2590	–0.0132	–0.4354	22,000
Bioethanol, L/h	0	1	–0.236	0	25,000
Biodiesel, L/h	0	0	1	0	20,000
Biogas, m^3/h	–0.02963	–0.003810	–0.004	1	1,000

Table 3 Normalized weights of the disruption scenarios

Scenario	p	Scenario	p	Scenario	p
Scenario 1	0.1288	Scenario 6	0.0252	Scenario 11	0.0233
Scenario 2	0.1934	Scenario 7	0.0425	Scenario 12	0.0233
Scenario 3	0.2856	Scenario 8	0.0363	Scenario 13	0.0225
Scenario 4	0.0797	Scenario 9	0.0277	Scenario 14	0.0247
Scenario 5	0.0267	Scenario 10	0.0374	Scenario 15	0.0228

After determining the baseline state of the bioenergy park, the number of possible disruption scenarios were identified. In each scenario, *j* number of bioenergy plants is assumed to be disrupted due to reduction in production capacity. For this particular case study, since the network is quite small, all the possible scenarios are enumerated. The next step in the risk analysis is to determine the probability of each scenario to occur. Subjective probabilities were determined using the pairwise comparison method commonly used in AHP. The resulting normalized weights of the scenarios are shown in Table 3 and are computed based on conventional AHP using the eigenvector method. The weights in this case study are to be interpreted as the probability of the *ith* disruption scenario to occur.

Figure 2 shows the plot of the disruption consequence of each scenario in the bioenergy park. If each disruption scenario will be assumed as an independent event with a probability of 1, the figure shows the range or the possible minimum and maximum net output loss in the bioenergy park. The figure also shows that the consequence of disruption generally increases with the number of disrupted plants. For scenarios with the same number of disrupted plants, the extent of consequence is determined by degree of network connectivity. Generally, disrupted plants which are highly-connected resulted in a greater net loss compared to those which are sparsely connected. This result is similarly observed in the vulnerability analysis of generic industrial ecosystems (Zhu and Ruth, 2013) and Kalundborg IS network (Channa and Kopra, 2014). A recent study even demonstrated that the criticality (i.e., impact of a unit's failure) of a component plant within a bioenergy park is affected by its degree of connectivity to other components (Benjamin et al., 2014).

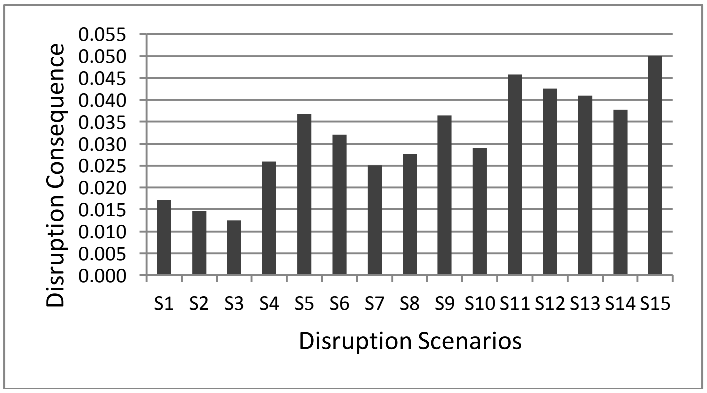

Figure 2: Disruption consequence of the bioenergy park disruption scenarios

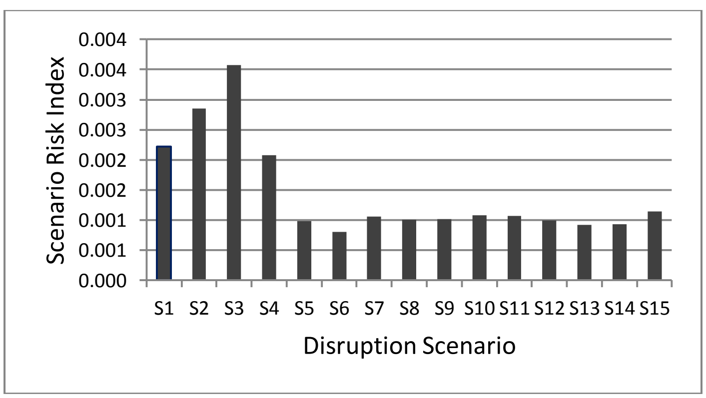

Figure 3: Risk index of the bioenergy park disruption scenarios

Figure 3 shows the different scenario risk indices. In this case study, it can be seen that the value of the risk index is greatly influenced by the probability of the scenario. Those low consequence scenarios but high in probability resulted in a higher risk index. This shows that the risk is higher for a single-plant failure event than a multiple-plant failure. Thus, greater risk management measures should be focused on the disruption of individual bioenergy plants compared to multiple-plant disruption scenarios. For this particular bioenergy park, scenario 3 or the disruption in the production capacity of the biodiesel plant has the highest risk index.

Finally, the multi-disruption risk index, R_M, for this particular bioenergy park is solved using Eq. (7). This index is the aggregate risk of the different disruption scenarios and weighted based on probability of occurrence. The total risk index for this case study is 0.0217, which is interpreted as a net output loss of about 2% from the baseline value. This risk information can be used by the risk analyst to create measures to reduce the network vulnerability against capacity disruptions.

4 CONCLUSIONS

A novel multi-disruption risk index for bioenergy parks was developed in this work. This index measures the aggregated and weighted net output loss of a bioenergy park based on exogenously-defined plant disruption scenarios. This network index is an important measure of the system's robustness to an array of probabilistic capacity disruption scenarios. This risk-based information can be used by bioenergy park owners in developing risk management strategies to reduce network vulnerability by increasing system redundancy and diversity. The significance of this multi-disruption risk index was demonstrated using a bioenergy park as a case study. The case study shows that the total network risk is greatly influenced by the probability of occurrence of the disruption scenarios. Future work will focus on developing network metrics on the resilience (i.e., dynamic recovery) of bioenergy parks from system disruptions.

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