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A Risk-based Criticality Analysis in Bioenergy Parks using P-graph Method

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The adoption of bioenergy parks is a prospective solution to increase the sustainability of stand-alone biomass processing plants. Production and resource efficiency, lower carbon emissions, and economic sustainability are achieved by synergistic exchanges of material and energy resources between components plants. However, such increased plant interdependency and the resulting integrated energy system is vulnerable to capacity disruptions. Cascading failure due to such disruptive event is an inherent risk in bioenergy parks and may pose as a barrier in implementing such system. The extent of risk originating from disrupted critical component plants in the network exhibited to be higher. A previous study developed a novel risk-based criticality index, based on input-output models, to quantify the effect of a component plant's disruption within a bioenergy park. This index is used to rank the plant's relative risk in the network based on its disruption consequence. In this work, a P-graph approach is proposed as an alternative methodology for criticality analysis of component plants in a bioenergy park. The P-graph framework is initially developed for solving process network synthesis, but recently being used to solve similarly structured problems. This risk-based metric can also be used for developing risk management measures to protect critical infrastructures, thereby increasing the robustness of bioenergy parks against disruptions. A case study is then presented to demonstrate the effectiveness of this method.

1. Introduction

Industrial symbiosis (IS) is a specific strategy of Industrial Ecology (IE) that aims to achieve sustainability through material and energy synergies (i.e., product, by-product, utility, and waste) between industrial plants (Chertow, 2000). Such network is characterized as having increased economic benefits and decreased environmental footprint for each component plant involved (Maille and Frayret, 2016). The synergistic links between industrial plants in an IS network increases the interdependencies between components and thus creating a highly integrated energy system (Zhu and Ruth, 2013). A bioenergy park in particular, is a type of IS network that is developed between independent biomass processing plants and other auxiliary industries (Benjamin et al., 2015a). Since the production of 1st generation biofuels are still confronted with several sustainability issues (e.g., high water footprint), the adoption of bioenergy parks is a potential solution to this problem (Martin and Eklund, 2011). Several studies have already demonstrated the advantages of implementing bioenergy parks; therefore, analyzing the risks involved prior to adopting such strategy is imperative. According to Seay and Badurdeen (2014), risk analysis should be an essential part of a sustainable integrated biofuel or bioenergy system (e.g., supply chains).
Risk analysis in bioenergy parks or IS networks in general, is an underdeveloped research area that needs sufficient underpinning discussions as potential risks as well as uncertainties in such system were already raised earlier (Boons et al., 2011). Risk analysis is a qualitative and quantitative tool to identify what can go wrong in a given system, determine the probability of such scenario, and measure the consequences of such

event. Sources of risks in IS networks are capacity disruptions (i.e., plant inoperability) resulting from reductions in the production level of component plants (Zhu and Ruth, 2013). According to Rinaldi et al. (2001), the risk of disruption is increased in interdependent networks due to propagation of failure. This happens when a disruption in one or more components in the network causes the failure of other components. The study of Zhu and Ruth (2013) demonstrated that IS networks suffer inherent vulnerability when subjected to component disruptions. Capacity disruptions within bioenergy parks affect the overall performance of the network due to decreased potential benefits for each component plant involved. Such disruption scenarios may be a barrier in adopting such system. Bioenergy parks specifically, are vulnerable to climate change-induced events such as drought and floods. These events may significantly reduce the supply of feedstocks for bioenergy production resulting to the disruption of the entire bioenergy park (Langholtz et al., 2014). Methods for systematic risk analysis should be therefore established prior to the creation of bioenergy parks.

Benjamin et al. (2015a) developed a criticality index for bioenergy parks, this risk-based metric measures the impact of a component's failure within the IS network. The criticality index was developed using input-output (I-O) analysis which is commonly used in analyzing the interdependency of economic systems (Leontief, 1936). I-O is a systematic method that can quantify linear relationships of interdependent components in a given system. In their work, criticality is defined as the measure to which a disrupted component plant is the source of network vulnerability (Benjamin et al., 2015a). This index can be used to rank the bioenergy plants within the bioenergy park to determine which components are relatively more critical in relation to their function in the entire network. The study of Benjamin et al. (2015b) demonstrated that the extent of damage is higher if the disruption originates from critical components (i.e., highly connected bioenergy plants) in the network. Therefore, the identification and subsequent protection of critical facilities in bioenergy parks are significant risk management steps in reducing system vulnerability due to disruptions.

In addition to I-O analysis, graph theory methods such as P-graph (process graph) can be used in analyzing potential risks in bioenergy parks (Klemeš and Varbanov, 2015). P-graph is a graph theory and combinatorial algorithm-based framework developed by Friedler et al. (1992a) for process network synthesis (PNS). This method is based on axioms and theorems that develops maximal structure, determines feasible structures, and solves optimal conditions of a given system (Friedler et al., 1993). Recently, the P-graph method is used to optimize disrupted integrated systems at different scales. This approach is applied to polygeneration systems under process inoperability conditions (Tan et al., 2014), allocation of electricity in economic sectors during climate change-induced crisis conditions (Aviso et al., 2015), allocation of inoperability in urban infrastructures (Tan et al., 2015), and to determine optimal "damage control" during crisis conditions in industrial complexes (Tan et al., 2015). However, to date, P-graph method has not been applied to develop risk-based metrics to determine the criticality of component plants within a bioenergy park.

In this work, we propose the use of P-graph in determining the criticality of components in a bioenergy park. This approach is similar to the method developed by Benjamin et al. (2015a) using I-O analysis. The rest of the article is organized as follows. A formal problem statement is given and the methodology describing the P-graph approach is presented in the next sections. A bioenergy park case study is then presented to demonstrate the methodology and the corresponding results similar to the I-O method are shown. Finally, conclusions and future research works are given towards the end of the paper.

2. Problem Statement

Criticality analysis in bioenergy parks using P-graph is similar to the method developed by Benjamin et al. (2015a). The bioenergy park is composed of *n* number of bioenergy plants and each is characterized by scale-invariant material and energy balance ratios. It is assumed that each component plant produces a main product stream (e.g., CHP plant produces Power). The baseline capacity or production level of each bioenergy plant will be determined using P-graph. We then assume, for a given scenario, that one component plant is disrupted (i.e., partially inoperable). The method used in this work also assumes that the reduction in the capacity of the component plant directly affects its final output stream. The change in the output of the affected stream is then determined using P-graph. To compute for the criticality index, the fractional change in the net output stream will be normalized by dividing it with the given fractional capacity reduction. This index will be used to rank the bioenergy plants to determine the most critical component in the entire network. Please see the work of Benjamin et al. (2015a) for a detailed discussion of the criticality analysis methodology. Figure 1 shows the general framework for criticality analysis using P-graph.

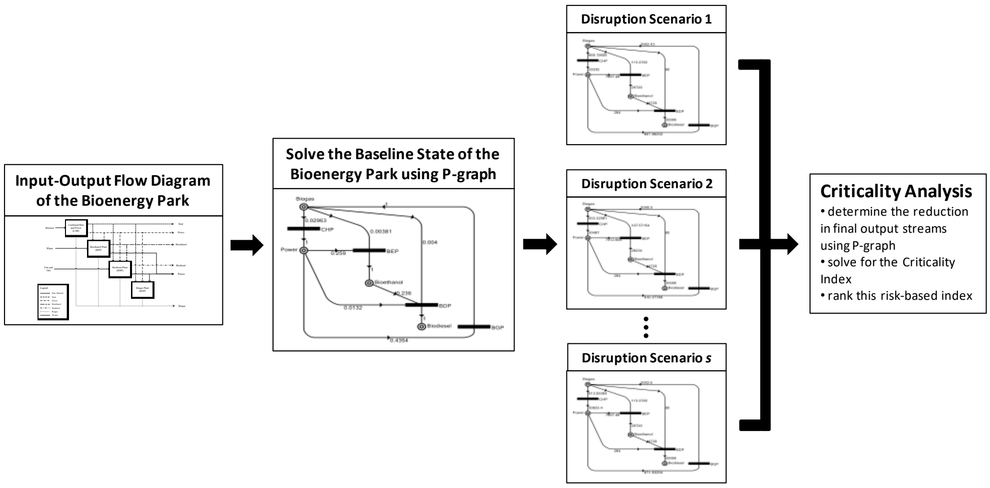

Figure 1: General framework for criticality analysis using P-graph

3. P-graph Methodology

P-graph is a graph theory and combinatorial algorithm based software used for solving PNS (Friedler et al., 1992b) and is a graphical version of mixed-integer linear programming (MILP) models. Compared to MILP, P-graph may generate more than one feasible solution (i.e., optimal and near-optimal) based on the objective function of the system. P-graph has two kinds of vertices which are the M-type and O-type vertices. The M-type or material type vertex represents material and energy streams in a system such as raw materials, intermediates, and products (e.g., bioenergy products). The O-type or operating unit type vertex represents the operating units (e.g., bioenergy plants) in the network. These vertices are connected by edges which represents the stream flowrates. The P-graph method follows five axioms to help determine the differences between vertices and to generate solution structures.

The P-graph method is based on following algorithms: the maximal structure generator (MSG), the solution structure generator (SSG), and the advanced branch-and-bound (ABB) algorithm. MSG generates the structure of the system which shows all possible connections in producing the final product. SSG generates all feasible subsets of MSG and ABB solves each subsets generated by SSG as a separate linear program to select the best solution. P-graph has two softwares used for designing process networks which are PNS Draw and PNS Studio. PNS Draw is used to create the interconnections between processes and the corresponding stream flowrates. PNS Studio is used to enter measurement units, stream flows, capacity of operating units, and the cost and prices of materials and operating units. The feasible solution/s generated is exported to PNS Draw to show the graphical representation of the corresponding solution/s. The developers of P-graph recently released an integrated version of the two software packages called P-Graph Studio.

In this work, P-graph method is used to solve for the final output stream which is affected by the disruption of a particular component plant in the bioenergy park. For each scenario, a disruption capacity constraint and final output stream constraints are directly encoded in the PNS Studio software. The resulting endogenous capacity of component plants and reduced final output of the affected product stream is then displayed after running the model.

4. Case Study: Bioenergy Park

The hypothetical bioenergy park case study is described in the work of Martin and Eklund (2011) with additional assumptions by Benjamin et al. (2015a). The bioenergy park shown in Figure 2 comprised of a 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 streams as their main product: power (P), bioethanol (E), biodiesel (D), and biogas (G) respectively. It can be seen from the figure that portion of the main products produced by a particular plant is being used by other plants within the network.

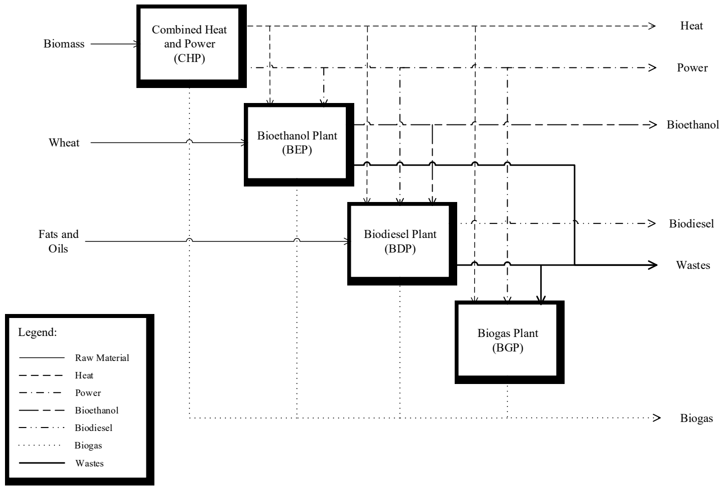

Figure 2: Process flow diagram of the bioenergy park

Table 1 shows the process data for the baseline state of the bioenergy park. Each of the first four data columns in the table is considered a process vector and contains fixed set of key material and energy balance ratios for each bioenergy plant. To illustrate connectivity, the BEP needs 0.2590 kW of power and 0.0038 m^3/h of biogas as inputs to produce 1 L/h of bioethanol. The last column in Table 1 also shows the final output streams of the network. The corresponding P-graph representation of the input and output flow of the bioenergy park is shown in Figure 3. The baseline production levels or capacities of the bioenergy plants are then determined using P-graph. This is accomplished using the PNS Draw and PNS Studio software. The solution is then presented in text format using PNS Studio or via a graphical version using PNS Draw. The results are shown in Table 2.

Table 1: Process data for the baseline state of the bioenergy park (adapted from Benjamin et al., 2015)

Product stream	CHP	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

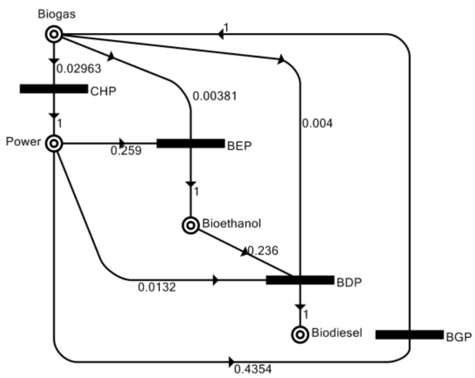

Figure 3: Input-output flow diagram of the bioenergy park using P-graph

Table 2: Baseline production levels of the bioenergy park

Bioenergy plant	CHP, kW	BEP, L/h	BDP, L/h	BGP, m^3/h
Plant capacity	30,879	29,720	20,000	2,108

After determining the baseline state of the bioenergy park, the criticality index of each bioenergy plant is determined using a 5 % reduction in production capacity. Four scenarios were used in this case study corresponding to the disruption of each component plant in the network. For each scenario, it is assumed that the disrupted bioenergy plant only affects its main product stream and that the final output of others streams are fixed. This approach allows the direct measurement of the impact of plant disruption to its final output.

The reduction in the final output stream per scenario was determined using P-graph. The final output is then computed by deducting all network internal requirements from the reduced production level of a particular component plant. The summary of the final output streams in the four scenarios and the corresponding fractional reduction is shown in Table 3.

Table 3: Fractional change in the final output streams of the disruption scenarios

Scenario	Disrupted component plant	Affected product stream	Baseline final output	Reduced final output	Fractional change
Scenario 1	CHP	Power, kW	22,000	20,476	0.069
Scenario 2	BEP	Bioethanol, L/h	25,000	23,514	0.059
Scenario 3	BDP	Biodiesel, L/h	20,000	19,000	0.050
Scenario 4	BGP	Biogas, m^3/h	1,000	896	0.104

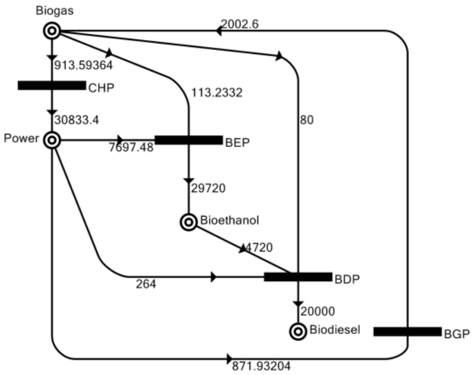

Figure 4: Disrupted state of the bioenergy park, Scenario 4

It can be seen from Table 3 that the disruption of the BGP resulted to the largest reduction in the final output. The disrupted state of the bioenergy due to the inoperability of the BGP is shown in Figure 4. The criticality index is calculated by dividing the fractional change by the fractional capacity reduction of 0.05. This risk-based index is then used to rank the bioenergy plants to determine the most critical component in the network and the results of these calculations are presented in Table 4. It can be seen from the table that the most critical component in the bioenergy park is the BGP. This suggests that a reduction in the production capacity of the biogas plant results to a greater net output loss compared to other product streams in the network. This information can be used by risk analyst to create measures to protect such critical infrastructure from disruption or create risk management strategies such as ensuring the reduced supply from this plant can be augmented using back-up or standby facilities.

This P-graph based method shows the equivalent results compared to the I-O method previously developed by Benjamin et al. (2015a). Aside from this, the use of P-graph's visual interface to encode data and display results is a practical advantage of this method.

Table 4: Criticality index and risk ranking of bioenergy plants

Rank	Criticality index	Scenario	Disrupted component plant
1	2.1	Scenario 4	BGP
2	1.4	Scenario 1	CHP
3	1.2	Scenario 2	BEP
4	1.0	Scenario 3	BDP

5. Conclusions

A P-graph based methodology for the criticality analysis of component plants in a bioenergy park was developed in this work. This risk-based approach is important in increasing network robustness through the creation of risk management strategies for identifying and protecting critical facilities in IS networks. The P-graph method was demonstrated using a case study from the work of Benjamin et al. (2015a). Equivalent results were obtained when compared to the previously used I-O approach. Future work will focus on extending this P-graph based method in risk analysis of regional biomass networks and bioenergy supply chains.

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