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Optimal Operations of a Bioenergy Park Under Capacity Disruptions via the P-graph Method

Michael Francis D. Benjamin[a,*], Kathleen B. Aviso[b], Beatriz A. Belmonte[a], Raymond R. Tan[b]

[a] Research Center for the Natural and Applied Sciences / Chemical Engineering Department, 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 typically composed of separate biomass-processing plants that have agreed to collaborate via material and energy product synergies to achieve more sustainable operations. The inability of one or more component plants to provide the agreed demand for a product will cause cascading disruptions in the entire network. The inoperability in a bioenergy plant can be caused by a reduction in available raw materials, internal equipment malfunctions, or delays in transporting goods within the supply chain. Despite the disruption, bioenergy parks can continue their operation by optimizing the network's allocation of the material streams. In this work, a P-graph method is developed to optimally adjust operations of a bioenergy park under capacity disruptions. This model considers the effects of deviating from the baseline demand by introducing a penalty rate. This penalty is a financial cost to be deducted from the bioenergy park's optimal economic potential as a result of not being able to meet contractual obligations. A bioenergy park case study is chosen to demonstrate the proposed methodology. Results show that there is about a three-fold further decrease in the optimal profit when penalty rates are applied in the model.

1. Introduction

Bioenergy parks are developed in response to the need to curb carbon emissions and increase resource efficiency in existing industrial parks. This specific type of eco-industrial park (EIP) was proposed by Martin and Eklund (2011) as a means for stand-alone bioenergy facilities to exchange material and energy products for achieving more sustainable operations. Such systems are already proven to have environmental, economic, and social benefits. Bioenergy parks are either formed via spontaneous, planned, or facilitated collaborations between facilities located in close proximity. These industrial symbiosis exchanges are typically accomplished through contracts and supply chain mechanisms within the network. Previous works on the design and analysis of EIPs include the use of social network analysis to measure network sustainability (Genc et al., 2019), multi-objective optimization for planning material networks (Valenzuela-Venegas et al., 2020), game theory in the optimal design of exchange networks (Salas et al., 2021), and decision-making support tools for EIPs in transition (Tseng et al., 2021).
Process graph (P-graph) approaches can also be used in the design and analysis of bioenergy parks. The P-graph method is developed using graph theory as well as efficient combinatorial algorithms that can be used in solving process network synthesis (PNS), such as planning a bioenergy park. One of the advantages of using this method is its adaptability and flexibility in solving various analogous problems, as presented in Friedler et al. (2019). Recent applications of P-graph are in the mapping of wastewater treatment facilities (Yenkie et al., 2021), causality maps for socio-technological systems (Tan et al., 2021), synthesizing polygeneration systems with negative emission technologies (Pimentel et al., 2021), and synthesis of integrated biorefineries (Sangalang et al., 2021). For bioenergy park design and analysis, Benjamin et al. (2017b) developed an equivalent input-output (I-O) based criticality analysis using P-graph. These studies only considered the impact of disruption to material and energy flows, and not on the economic potential. The economic potential refers to the difference in total sales of products and the total costs of purchasing the input materials. Such parameter should be

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considered during the planning and design stage of bioenergy parks as network disruptions may potentially occur and affect the economic aspect.

EIPs and bioenergy parks should be designed to withstand various disruptions to ensure sustainable operations, specifically in producing the required amount of products. Capacity disruptions in bioenergy plants can be due to decreased raw material inputs or variability in biomass supply (Benjamin et al., 2017a). This disruption can also be caused by internal equipment or process unit failure within a particular facility in the bioenergy park. Such failures propagate within the EIP network, and this would affect its sustainability (Valenzuela-Venegas et al., 2020). The decreased production capacity will affect the ability of the bioenergy park to fulfil its commitment to supply the material or energy exchanges within the network; this will also result in not delivering the required demand from customers outside the bioenergy park. In such cases, financial penalties could be imposed to compensate for the losses incurred by the customers. Gumilao et al. (2020) used this to account for financial penalties during abnormal operations of an industrial plant. The use of P-graph to optimally synthesize a bioenergy park and consider penalty rates are not yet implemented.

A P-graph based method to determine optimal operational modifications in a disrupted bioenergy park considering economic potential and financial penalties is developed in this study. Without this work, there will be an overestimate of the profit for the bioenergy park as customers may seek financial remuneration later on for not meeting the agreed-upon contracts. The method ensures optimal allocation of product streams during abnormal conditions of the network caused by capacity reductions. This work is an extension of the approach of Gumilao et al. (2020) but applied to the industrial park level and via the P-graph methodology. The rest of the paper is presented in the following manner. The problem statement discusses the key assumptions and research gaps being addressed. The P-graph based method is then presented, and the corresponding case study using a bioenergy park is used to demonstrate the proposed approach. Finally, the conclusions and future research directions are outlined.

2. Formal problem statement

The problem statement and assumptions used in this study are presented in this section. The bioenergy park consists of *n* number of component plants with *p* number of product streams. The fixed material and energy I-O ratios for each bioenergy component plant and the connections within the network are given. The corresponding unit price of raw materials and product streams were taken from current market conditions. The bioenergy park's baseline state, including the plant capacity, product stream rates, and optimal hourly profit, are determined via P-graph using a predetermined amount of raw material inputs. There will be *s* number of disruption (i.e., single-plant) scenarios equal to the number of existing component plants. A reduced capacity of a particular bioenergy plant will be encoded in the software; such a scenario is possible when there is a reduction of available feedstock or process unit malfunction within the facility. The problem is determining the optimal operational adjustment of component plants and allocation of streams within the network to maximize the hourly profit of the bioenergy park. Profit in this work is similarly defined as that of economic potential. The economic potential is defined as total revenues from the sale of products or by-products minus the total cost of purchasing the raw materials. The actual profit of the bioenergy park will be lesser if investment and operational costs will be considered; these values are not yet incorporated in this work. Using a penalty rate for each product stream, the adjusted economic potential is calculated based on the deviation from the baseline value of the product streams. A penalty rate is a financial obligation paid to customers for not being able to deliver the agreed-upon amount of product. The general framework used in this study is presented in Figure 1.

3. P-graph methodology

This part presents the P-graph approach that will be used in the study. The paper of Friedler et al. (1992b) presents the development the P-graph methodology, three decades ago, for process network synthesis (PNS) problems. The combinatorial algorithm-based and graph theory-based method is founded upon five axioms and three efficient algorithms Friedler et al. (1992a). Graphical solution structures are generated by the P-graph Studio software, an advantage over the conventional mixed-integer linear programming (MILP) tools. Aside from this, optimal and sub-optimal structures can be determined; this feature is not explicit in MILP-based tools. Recent features of the software include solving time-constrained synthesis, multi-stage approaches, and multi-period problems.

The bipartite graph can be constructed by connecting vertices using arcs (i.e., links or connectors). The two types of vertices include the M-type (i.e., material) and the O-type (operation or process). The M-type in this work are the raw materials or product streams, and the O-type represents the biomass processing plants in the bioenergy park. The component algorithms of the P-graph framework are as follows. A rigorous, error-free superstructure is generated by the Maximal Structure Generation (MSG) algorithm; all the possible pathways for producing a specific product are considered. The Solution Structure Generation (SSG) algorithm enumerates all structurally feasible networks. The optimal and near-optimal solutions, can be determined using the Accelerated Branch-and-Bound (ABB) algorithm using flow and cost data coupled with structural information. The step-by-step procedure of using the P-graph method is in the paper Lam et al. (2016).

In this work, the I-O ratios of the bioenergy plant and the amount of raw materials are inputted in the P-graph Studio software (P-graph, 2021). The model will determine the optimal hourly profit, the capacity of component plants, and baseline product rates. Using the optimal solution, a reduced capacity is encoded in the specific bioenergy plant per scenario. This is to determine the deviation in the resulting product streams. The new optimal solution is solved under capacity disruption, and the penalty rate is applied for those product streams with values less than the baseline. The adjusted optimal hourly profit is then calculated.

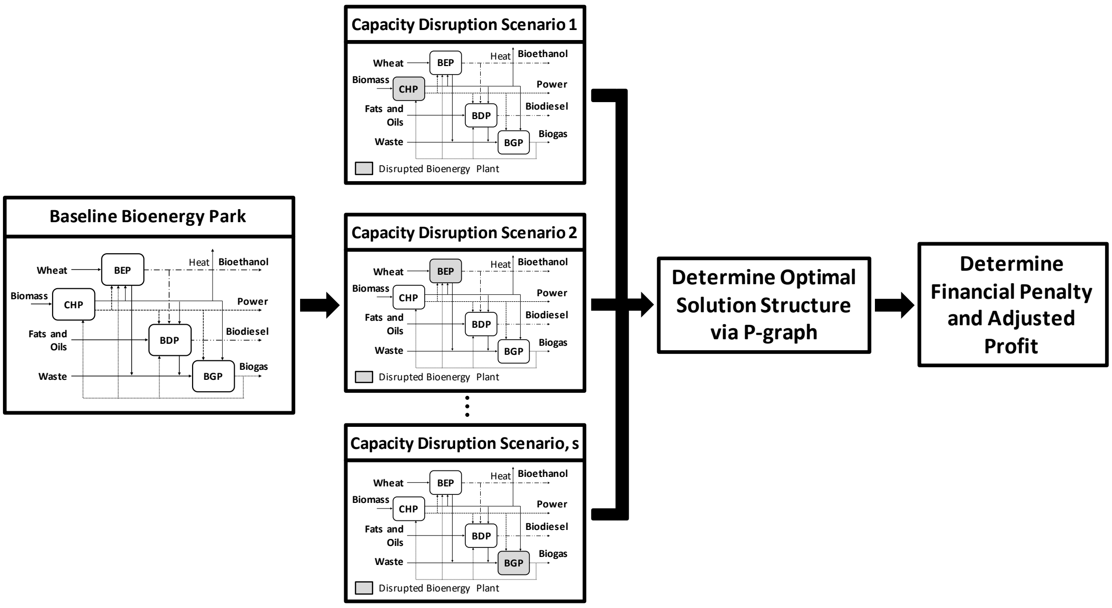

Figure 1: Overall framework for optimal operations of a bioenergy park under capacity disruptions

4. Bioenergy park case study

The hypothetical bioenergy park utilized as a case study was derived from Benjamin et al. (2015). The bioenergy-based eco-industrial park or complex consists of several component plants that produce conventional biofuels. Wheat is being used to produce 1st generation bioethanol, and fats and oils are processed to produce biodiesel. Several waste outside the park and from within are being processed and upgraded to biogas. A biomass-based CHP is included in the bioenergy park to ensure the supply of the needed power and heat by the other facilities. The products of the bioenergy park are being consumed internally, and any excess are sold outside the industrial park based on customer demands. A baseline demand or final output for products is normally set, and a deviation from this value may incur financial penalties. This is due to the inability of the bioenergy park to supply the needed amount of products based on agreed-upon contracts.

The I-O material and energy ratios of each bioenergy plant are presented as columns in Table 1. A positive value specifies that it is a product from that facility and a negative value suggests that it is being used as a raw material. The values in the table are already normalized per amount of main product stream being produced by a specific bioenergy plant. The following amounts of raw materials are used: 78.12 t/h wheat, 51.7 t/h biomass, 18,520 L/h fats and oils, and 6.98 t/h waste. The P-graph version of the network is shown in Figure 2. Table 2 shows the raw material and product stream price per unit. The values were taken from various published literature and are based on current market conditions. These values will be entered as constraints in the P-graph software to determine the baseline production capacity of plants and final output of bioenergy product streams. The baseline capacities of the bioenergy plants are as follows: 30,881 kW for combined heat and power plant (CHP), 29,720 L/h for bioethanol plant (BEP), 20,000 L/h for biodiesel plant (BDP), and 2,108 m^3/h for the biogas plant (BGP). The baseline final output for each product stream are 22,000 kW power, 25,000 L/h bioethanol, 20,000 L/h biodiesel, 3,723 kW heat, and 1,000 m^3/h of biogas output.

The unit penalty for each product stream is also shown in Table 2; the financial penalty varies between 7 % to 10 % more than the original unit price. The penalty rate per product stream is computed by multiplying the unit penalty by the difference between the baseline net output and the actual net output per scenario. These values will then be deducted from the optimal hourly profit per scenario to determine the adjusted economic potential of the bioenergy park. In the four scenarios, a hypothetical 5 % reduction in capacity will be encoded for a specific bioenergy plant as a constraint in the P-graph software, and the new optimal structure will be determined. The list of scenarios and the value of the disrupted capacity are presented in Table 3. This approach is used to determine how critical is the component plant in terms of its impact on the overall profit. The method was derived from the criticality analysis (Benjamin et al., 2015), which initially considered the reduction in flows.

Table 1: Input-output data for the case study's baseline state (Benjamin et al., 2015).

Product stream	CHP (kW)	BEP (L/h)	BDP (L/h)	BGP (m^3/h)
Power, kW	1.0000	–0.2591	–0.0132	–0.4354
Bioethanol, L/h	0	1.0000	–0.2360	0
Biodiesel, L/h	0	0	1.0000	0
Biogas, m^3/h	–0.0296	–0.0038	–0.0040	1.0000
Wheat, t/h	0	–0.0026	0	0
Biomass, t/h	–0.0017	0	0	0
Fats and oils, L/h	0	0	–0.9260	0
Waste, t/h	0	0.0001	0.0004	–0.0085
Heat, kW	1.8519	–1.5238	–0.1489	–2.4662

Table 2: Unit price of materials and products, and unit penalty used in the case study

Material and product stream	Price (USD/unit)	Penalty (USD/unit)
Power, kW	0.1458	0.1562
Bioethanol, L/h	1.1861	1.2903
Biodiesel, L/h	1.3000	1.4041
Biogas, m^3/h	0.5000	0.5500
Wheat, t/h	195.30	N/A
Biomass, t/h	25.000	N/A
Fats and oils, L/h	0.5000	N/A
Waste, t/h	5.0000	N/A
Heat, kW	0.0600	0.0652

Table 3: Optimal profit of the baseline and capacity disruption scenarios

Scenario / disrupted bioenergy plant	Disrupted capacity	Optimal hourly profit (USD/h)	Penalty rate (USD/h)	Adjusted optimal hourly profit (USD/h)
Baseline scenario	N/A	33,739.00	N/A	33,739.00
Scenario 1: CHP (kW)	29,336.95	33,429.90	427.56	33,002.34
Scenario 2: BEP (L/h)	28,234.00	32,928.90	1,924.47	31,004.43
Scenario 3: BDP (L/h)	19,000.00	33,181.50	1,427.29	31,754.21
Scenario 4: BGP (m^3/h)	2,002.60	33,713.10	58.08	33,655.02

The optimal hourly profit of the baseline scenario (i.e., no capacity disruption) and the four scenarios are presented in Table 3. The profit of the baseline scenario is 33,739 USD/h. The incurred financial penalty and the adjusted profit are also shown. For Scenario 1, also shown in Figure 3, the reduced capacity of the CHP produced a decrease in the net output of power and heat. The combined penalty is 427.56 USD/h. For Scenario 2, the high penalty is caused by the significant decrease in biodiesel output. The total penalty for this commodity is 1,917.39 USD/h. In Scenario 3, while the production of the BGP is affected, the large penalty is driven by the losses in biodiesel output which is about 1,404.10 USD/h. Lastly, for Scenario 4, the only product stream affected is the biogas, and the resulting penalty is 58.08 USD/h. Using the results from Table 3, without penalty, the deviation from the optimal baseline profit was 0.08 % (Scenario 4) to 2.40 % (Scenario 2). When the penalty rates are applied, this results in a reduction of 0.25 % (Scenario 4) to 8.11 % (Scenario 2) in terms of profit. Based on the results, the disruption of the BGP will result in the least deviation from the optimal baseline profit, and the most significant reduction in profit is when the BEP is disrupted. The financial risk caused by capacity reduction can be minimized by having multiple sources of raw materials or feedstock and having redundancy mechanisms in case of equipment malfunction. While the financial penalties used in this case study are relatively small, this may significantly impact an industrial setting since supply chains which are more complex and may not tolerate slight deviations in product demand contracts.

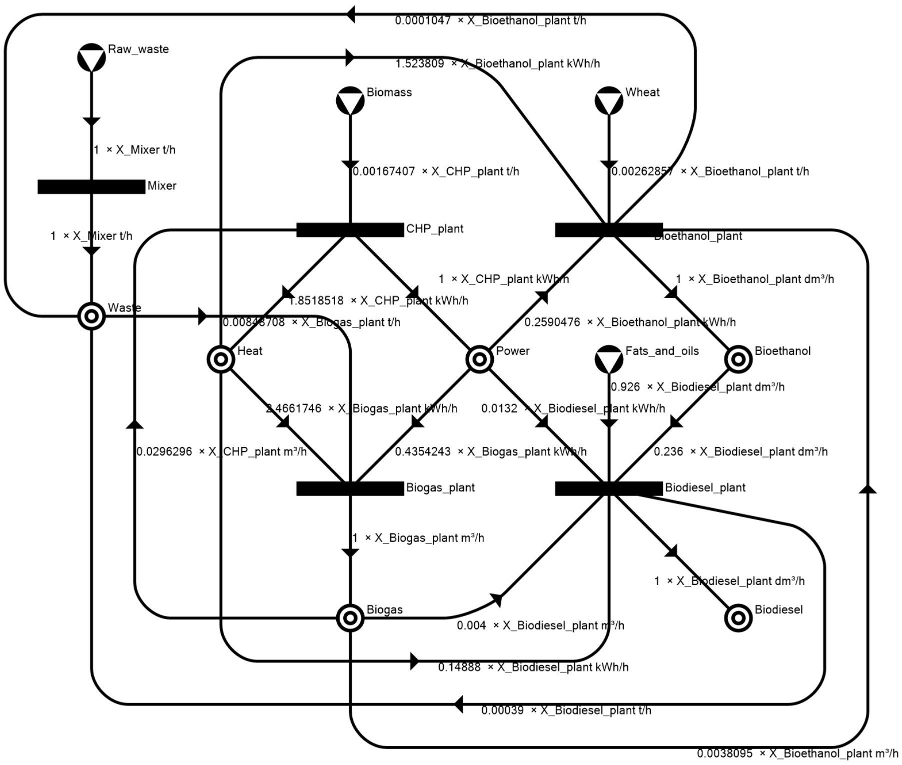

Figure 2: P-graph representation of the bioenergy-based eco-industrial park

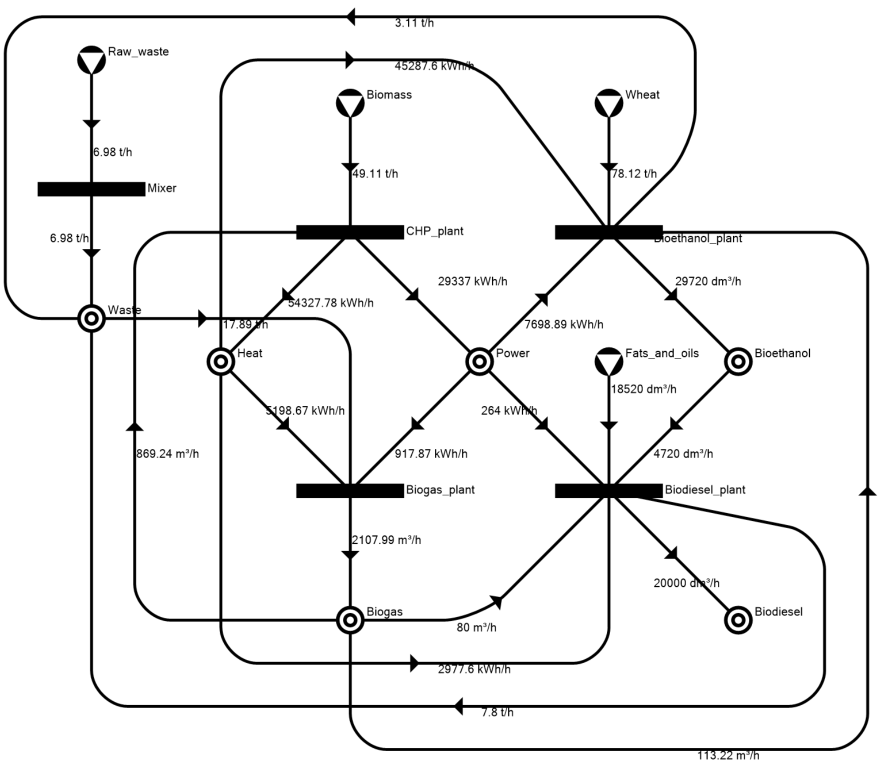

Figure 3: Optimal solution structure of the bioenergy-based eco-industrial park in Scenario 1

5. Conclusions

In this work, a P-graph based method was developed for determining the optimal operating states of a disrupted bioenergy park. The approach determines the optimal hourly profit of the eco-industrial park and accounts for the deviation in net output by introducing a penalty rate. The penalty rate is compensation paid to customers for losses incurred in not meeting the contractual obligation. The approach is an extension based from the method developed by Gumilao et al. (2020) that was initially used for an industrial plant. One of the advantages of using this method includes the immediate display of the optimal network structure upon changes in one or more parameters. The proposed method is applied using a bioenergy park as a case study. Future work will incorporate penalty rates for multi-disruption and multi-period problems.

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