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Resources Allocation and Operations Optimization for CO_2 Capture in Industrial Clusters

Yick Eu Chew[a], Bing Shen How[a], Irene Moser[b], Michael Francis D. Benjamin[c], Raymond R. Tan[d], Viknesh Andiappan[a,*]

[a] Research Centre for Sustainable Technologies, Faculty of Engineering, Computing and Science, Swinburne University of Technology Sarawak, Jalan Simpang Tiga, 93350, Kuching, Sarawak, Malaysia.
[b] School of Software and Electrical Engineering, Swinburne University of Technology, Melbourne, Victoria, 3122, Australia.
[c] Research Center for the Natural and Applied Sciences/Chemical Engineering Department, University of Santo Tomas, España Blvd., 1015, Manila, Philippines.
[d] Department of Chemical Engineering, Gokongwei College of Engineering, De La Salle University, 2401 Taft Avenue, 0922 Manila Philippines.
vmurugappan@swinburne.edu.my

Industries with hard-to-abate emissions are a significant source of global carbon dioxide (CO_2) emissions. CO_2 capture infrastructure offers opportunities to reduce emissions from processes that are hard to decarbonize. However, the high cost of implementing CO_2 capture infrastructure on-site remains a barrier. An industrial cluster offers a more economical alternative, by enabling multiple plants to share energy systems and CO_2 capture infrastructure. Infrastructure sharing poses financial and operational risks when disruption occurs in one of the participating plants in the industrial cluster. The decision on which plants to prioritize or to scale down during such a disruption becomes crucial in minimizing operational losses. For effective operations and resource management, it is important to consider compensation required, energy loss and CO_2 deficit removal within an industrial cluster. To address this, a two-stage mixed-integer linear programming optimization model is developed to determine an optimal resource distribution scheme through the Shapley value calculation. The model is demonstrated through a case study where the impact of a gas turbine failure on an industrial cluster is evaluated. The results show that forming a coalition lowers total compensation to \$ 268.6 k, compared to \$ 677.1 k when plants are compensated individually. Based on the Shapley value, the ammonia plant receives 27.0 %, the cement plant 25.5 %, and the iron and steel plant 47.5 % of the total compensation. The second-stage optimization further refines results by diversifying the energy loss and CO_2 removal deficit across plants based on their received compensation. This yields a net compensation satisfaction level of 0.458.

1. Introduction

Carbon-intensive sectors urgently require effective solutions to reduce their CO_2 footprint. CO_2 capture infrastructure has emerged as a promising strategy to help these sectors for decarbonization. However, the high costs of implementing CO_2 capture infrastructure often make it economically challenging for a single plant to adopt such technologies on its own. A more practical approach to overcome the issues is by integrating CO_2 capture infrastructure within an industrial cluster. The plants within the industrial work together by sharing infrastructures and exchanging resources such as energy, water and raw materials. This collaborative effort not only lowers the cost of CO_2 capture and transport but also enhances the overall efficiency of resource use. As a result, industrial clusters offer both economic and environmental advantages.

Nevertheless, the formation of industrial cluster also brings new challenges due to their high interdependency. A key concern is the heavy reliance on shared facilities such as decentralized energy systems that supply power to several plants and capture CO_2 capture infrastructure to sequester CO_2 from those plants at once. A single equipment failure can disrupt the entire industrial cluster's ability to generate sufficient power and meet emissions targets. Past works have explored different strategies to make these systems more robust during disruptions. Almoghathawi et al. (2019) examined the interruptions in a linked power and gas network that can

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affect the infrastructure network. The model aimed to maximize the overall resilience while minimizing recovery costs and time. Aviso et al. (2020) developed a fuzzy P-graph model to optimize off-grid renewable energy systems that include small hydroelectric plants by adapting their operation to community demand under varying water levels during droughts or other operational issues. A Monte Carlo simulation–based risk analysis tool was introduced by Benjamin et al. (2021) to evaluate how integrated bioenergy networks respond to supply chain disruptions. These studies focused on managing disruptions within individual facilities or single entities only. However, the complexity stakeholders' behaviour in forming coalition that arises when multiple plants are interconnected through shared infrastructure in industrial clusters and is overlooked.

Cooperative game theory has been applied to analyze how economic benefits from collaboration should be distributed among multiple stakeholders within the industrial clusters. For example, cooperative game theory is used in cost-sharing among waste producers to improve financial viability (Eryganov et al., 2020), profit allocation among internal processes to identify key drivers for optimizing integrated palm-oil based complex (Tan et al., 2020) and facilitating peer-to-peer energy trading to reduce bills and emissions (Kong et al., 2022). Limited attention has been given to resource allocation and operational management when failure occurs in shared facilities of an industrial cluster. The resource allocation and operational management here entails the allocation of compensation, distribution of energy loss and CO_2 removal deficits. This is important as failure in shared equipment within the industrial cluster would lead to energy shortages in participated plants, requiring compensation to obtain energy and offset the CO_2 removal deficit externally. In such events, decisions must be made on how to allocate financial compensation, manage disruptions in energy supply, and address CO_2 removal deficit among the multiple plants in the industrial clusters. These impacts are often distributed unevenly. Some plants may receive higher compensation while incurring fewer energy losses or emission responsibilities, whereas others may bear a disproportionate share of the burden. Without a fair and transparent allocation mechanism, such imbalances can lead to conflict, hinder cooperation, and ultimately compromise the stability of the entire cluster. This paper addresses this gap by developing a resource allocation procedure based on the Shapley value and from cooperative game theory (Shapley, 1951) coupled with two-stage sequential optimization. The method aims to fairly allocate both the limited energy supply and the compensation among all plants during disruption, based on their roles and contributions within the industrial cluster.

2. Methodology

Figure 1 presents the overall framework for this study. Material and energy balance within the cluster is modelled based on a superstructure of the industrial cluster using mixed-integer linear programming. The time period, denoted as $t \in T$, varies depending on the needs of the case study that can range from hourly to daily scales. The coalition, represented as $g \in G$, consists of a group of participating plants r within the industrial cluster that agree to work together and distribute the resources during times of shortage. These plants are required to adjust their operations to distribute the remaining energy available, especially when the equipment in the energy system is facing disruptions.

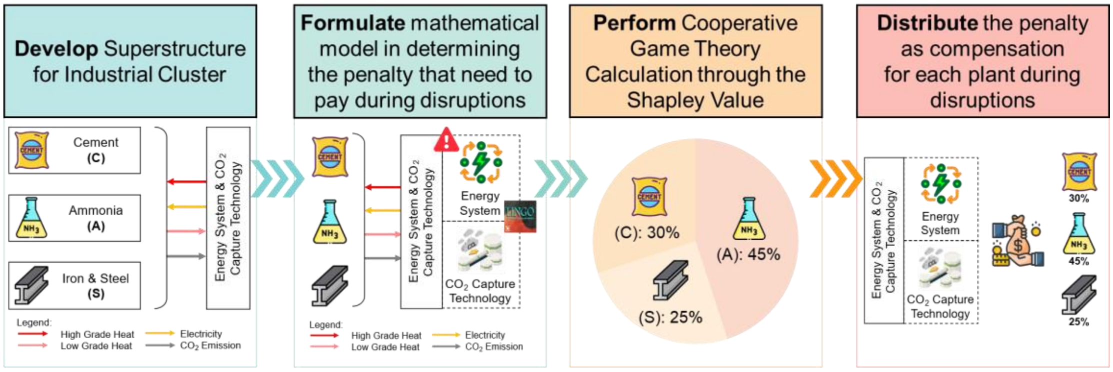

Figure 1: Framework for resource allocation and operations optimization in industrial clusters under disruption

In this study, the multi-period equations used to represent the interaction between the energy system and industrial plants are adapted from Chew et al. (2025). Before introducing the objective of the model, it is necessary to first determine the CO_2 removal cost that each of the participating plants would incur to reduce their CO_2 emissions. The cost represents the amount each plant needs to spend if it were to act independently or work together in a coalition. It is calculated based on the capital and operating costs of building a smart energy hub and implementing its decarbonization strategies. The objective of this model is to minimize the total cost (EXP_g) resulting from system disruptions as shown in Eq(1). These costs include the operational cost of the energy system ($OPEX_g$), cost of raw materials (RMC_g), revenue due to self-generating utilities ($REVENUE_g$), carbon pricing (CP_g) and compensation paid to each participating plant ($COMP_g$). It is important to note that the calculations for the first four terms which were detailed in Chew et al. (2025), will not be repeated in this paper. Whereas for the compensation ($COMP_g$), it can be determined using Eq(2). $COMP_g$ is the amount of money required by the energy system operator to pay to the participating plant *r* in a coalition when energy supply is reduced due to disruption. It includes three main components: the cost of purchasing electricity from external source ($ELEC_g^{Out}$), maximum demand charges associated with the electricity ($ELEC_g^{MaxDemand}$) and the penalty for not capturing the CO2 emissions ($CO2_g^{Penalty}$) in coalition *g*. The first two components are determined based on the flow rate of electricity purchased from external sources. The third component, $CO2_g^{Penalty}$ reflects the penalty incurred based on the CO2 removal cost and amount of CO2 not captured during disruptions. This term also accounts for the indirect emissions attributed to the consumption of external electricity which is associated with a higher CO2 intensity compared to the energy generated from shared energy system in industrial cluster. The compensation is calculated for different coalitions. These values are then used as the characteristics function (φ) to determine the Shapley Value (V_r) for each plant as described in Eq(3). The Shapley value is a pivotal concept in transferable utility cooperative games which provides a logical basis for computing fair shares of costs and benefits among players in a coalition (Shapley, 1951). The variable b represents the size of the coalition, while n denotes the total number of plants involved in the system. Characteristic function represents the total value or payoff that a coalition of plants can generate by working together. In this case, a coalition consists of the plants that share energy loss. This could mean a single plant handling the entire energy loss solely or multiple plants cooperating to distribute the energy loss. Once the total payoff in terms compensation ($Payoff_g^{Total}$) is calculated, the Shapley value is applied to fairly divide this amount ($Payoff_{rg}$) among the plants as shown in Eq(4). The distribution is based on the individual contribution of each plant to the coalition. Eq(4) applies only to coalitions of two or more plants and not to single plants acting alone (i.e., $g > 1$).

$$\min EXP_g = OPEX_g + RMC_g - REVENUE_g + CP_g + COMP_g \quad \forall g \tag{1}$$

$$COMP_g = ELEC_g^{Out} + ELEC_g^{MaxDemand} + CO2_g^{Penalty} \quad \forall g \tag{2}$$

$$V_r = \sum_{b=1}^{B} \frac{(b-1)!\,(n-b)!}{n!} \left[\varphi\{G\} - \varphi\{G-r\}\right] \quad \forall r \tag{3}$$

$$Payoff_{rg} = V_r \times Payoff_g^{Total}\Big|_{g\neq 1} \quad \forall r \ \forall g \tag{4}$$

The initial payoff only shows the total compensation received by each plant and does not allocate how much energy loss and CO2 emissions removal deficit that each plant must cover. To solve this, a second optimization step, Eq(5) is introduced. This step employs fuzzy optimization to merge multiple objectives into a continuous membership function (λ). A high λ reflects high satisfaction for each plant. This means that the net compensation that each plant can receive ($COMP_r^{Net}$) should be increased to the greatest extent as expressed in Eq(6). At the same time, the CO2 emissions removal deficit ($CO2_r$) should be maintained at a minimal level as described in Eq(7). This sequential optimization ensures each plant achieves the highest satisfaction by balancing the compensation they receive with the energy loss and CO2 removal deficit that each plant is responsible for. Note that $COMP_r^{Net}$ represents the compensation received by each plant after accounting for the costs associated with the outsourced electricity and CO2 services as displayed in Eq(8).

$$\max \lambda \tag{5}$$

$$\lambda \leq \frac{COMP_r^{Net} - COMP_r^{Net,Min}}{COMP_r^{Net,Max} - COMP_r^{Net,Min}} \quad \forall r \tag{6}$$

$$\lambda \leq \frac{CO2_r^{Max} - CO2_r}{CO2_r^{Max} - CO2_r^{Min}} \quad \forall r \tag{7}$$

$$COMP_r^{Net} = COMP_r - ELEC_r^{Out} - ELEC_r^{MaxDemand} - CO2_r^{Penalty} \quad \forall r \tag{8}$$

The equations formulated in this section are modelled in daily-basis and solved using Global Solver in LINGO V16.0 (LINDO Systems Inc, 2016).

3. Case Study

The case study examines industrial cluster that is made up of an ammonia plant, a cement plant, an iron and steel plant alongside a shared energy system and CO_2 capture infrastructure. Figure 2 presents the superstructure of the industrial cluster. The energy system involves two components: generation and consumption. On the generation side, it uses solar panels, combined heat and power units (including steam turbines, gas turbines, and gas engines), and an organic Rankine cycle (ORC) to recover waste heat. For consumption side, pelletizers and briquetting machines use electricity to convert biomass into low-carbon alternative fuels to be supplied to the plants. Whereas CO_2 capture infrastructure transport and store CO_2 emissions. These energy systems and CO_2 capture infrastructure will supply electricity and high-grade heat via low-carbon alternative fuels to the plants in a coalition. In return, the participating plants deliver back the waste heat to produce more electricity through ORC along with the CO_2 to be transported and stored.

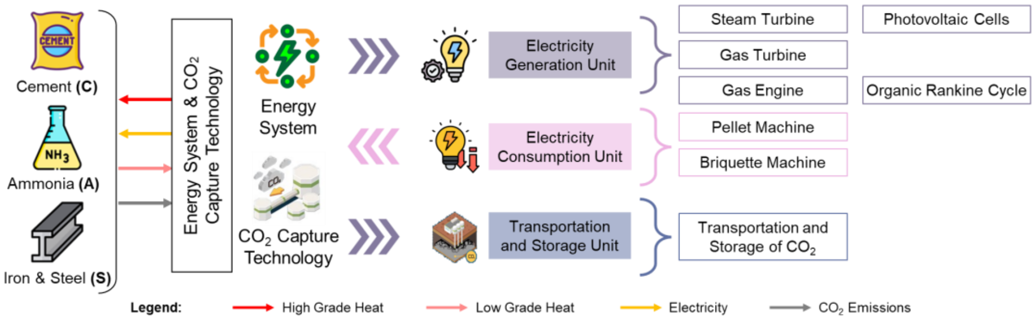

Figure 2: Superstructure of the Industrial Cluster

Table 1 summarizes the key data for each plant, with all values calculated after considering the range of possible decarbonization strategies. Table 2 presents the average daily solar intensity alongside the assumed production capacity of each facility. The solar intensity values are drawn from real-world statistical records, while the production capacities are estimated based on typical daily output. Table 3 provides information on the production capacity of the electricity generation units and the number of units needed to meet the energy demand of the industrial cluster. Note that these values are hypothetical. Additional details such as cost and efficiency of the equipment can be found in Chew et al. (2025). The case study aims to establish a fair allocation of resources, including compensation, energy loss, and CO_2 removal deficits, among cluster plants during a gas turbine disruption. Compensation is calculated using the Shapley value. Energy loss and CO_2 removal deficits are allocated through sequential optimization, as the two variables are interdependent.

Table 1: Production capacity, CO_2 emissions intensity, and energy demand for the plant involved.

Item		Ammonia (Appl, 1999)	Cement (Deolalkar, 2009)	Iron & Steel (Talaei et al., 2020)
Average Production Capacity (t/d)		2,000	3,000	3,500
CO_2 Emissions Intensity (tCO_2/t product)		1.62	0.57	1.47
Energy Demand (GJ/t product)	High-Grade-Heat	6.27	1.96	13.73
	Low-Grade Heat	-1.60	-	-
	Electricity	0.38	0.16	1.19

Table 2: Daily solar intensity and production capacity of the plant involved.

Time Period	Daily Solar Intensity (kWh/m^2d) (Solcast, 2024)	Production Capacity (t/d)		
		Ammonia	Cement	Iron and Steel
t1	6.07	2,169	2,156	3,550
t2	4.56	1,931	3,020	3,091
t3	3.76	1,568	3,087	2,578
t4	5.71	2,680	3,970	4,718
t5	4.51	1,286	2,939	2,819
t6	5.06	2,210	2,522	3,327
t7	5.19	2,155	3,306	4,418

Table 3: Production capacity of electricity generation units and the number of units required

	Steam Turbine	Gas Turbine	Gas Engine	ORC
Production Capacity (kW)	12,000	13,000	4,000	9,600
Number of Unit	2	1	6	4

4. Results and Discussion

Table 4 outlines the CO_2 removal cost under different coalitions of plants, which include individual efforts and collaboration between multiple plants. For example, if the ammonia plant ([A]) decarbonizes on its own, the cost is 56.0 \$/t-CO_2. If all three plants ([ACS]) worked together, the CO_2 removal cost will be 52.8 \$/t-CO_2. Two-plant coalitions are assessed solely to evaluate each participant's marginal contribution, and do not represent the final industrial cluster structure. These CO_2 removal costs guide how the energy system operator compensates plants whether a single plant or multiple plants share the CO_2 deficit and offset it through external services.
When the gas turbine in the energy system fails to operate, it results in a loss of 13,000 kW of electricity, which accounts for 14.1 % of the total power supply. To maintain operations across all plants in the industrial cluster, this power loss must be sourced from external providers. In addition, the power shortage also affects the CO_2 capture process since the system is unable to fully transport and store the CO_2 as initially planned when the energy availability is limited. Consequently, the energy system operator must pay some money to the plants, compensating them for the need to source both electricity and CO_2 removal services externally. The details of this compensation are provided in Table 4. If the ammonia plant alone takes on the energy loss caused by the gas turbine failure, it will receive compensation of \$ 207.3 k. However, if all three plants share the energy loss together, the total compensation they would receive collectively amounts to \$ 268.6 k.

Table 4: CO_2 removal cost and compensation that energy system operators need to pay for different coalition scenarios.

Coalition	[A]	[C]	[S]	[AC]	[AS]	[CS]	[ACS]
CO_2 removal cost (\$/t-CO_2)	56.0	74.2	121.4	47.3	53.3	120.2	52.8
Compensation Received (\$ k)	207.3	181.5	288.3	258.5	269.6	287.1	268.6

The total compensation of \$ 268.6 k is distributed among the three plants using the Shapley value method as outlined in Eq(3) and Eq(4). The results of this allocation are shown in Table 5. According to the calculations, the ammonia plant receives 27.0 % of the compensation, the cement plant receives 25.5 %, and remainders allocated for the iron and steel plant. In this context, marginal contribution of a plant refers to how its inclusion in a coalition changes the total compensation received. Note that this compensation is affected by the CO_2 removal cost as described in Eq(2). If forming a coalition lowers the total compensation, the plant has less marginal contribution and requires less compensation. On the other hand, if it raises the total compensation, the marginal contribution is higher, and more compensation is needed to ensure the plant remains in coalition. The cement plant receives the smallest share because its role in managing or absorbing the disruption is relatively limited when compared to others. In contrast, the iron and steel plant have the highest marginal contribution due to its larger CO_2 removal costs and higher energy demand that are affected during disruptions. When all three plants absorb the energy loss together, the iron and steel plant adjust its production to source more energy externally. This frees up more energy internally for the CO_2 capture infrastructure for other two plants, allowing for a better CO_2 management. Following the second stage of optimization, the final compensation each plant received considering the cost of electricity and CO_2 management from external sources is as follows: the ammonia plant receives \$ 2.0 k, the cement plant receives \$ 3.6 k, and the iron and steel plant receives \$ 25.9 k. With these compensations, the CO_2 emissions that each plant must offset from external sources are 543 t for the ammonia plant, 778 t for the cement plant, and 523 t for the iron and steel plant. In terms of electricity, the ammonia plant, cement plant, and iron and steel plant will need to obtain 653 MWh, 474 MWh, and 1057 MWh, respectively from external sources. The satisfaction level for net compensation is 0.458. However, if sequential optimization is not applied, the satisfaction of CO_2 removal deficit will drop from 0.458 to 0.363. In other words, without sequential optimization, some plants will bear more CO_2 removal deficit, which raises equity concerns. These results demonstrate that forming a coalition among three plants, shared energy system and CO_2 capture infrastructure helps to reduce the burden caused by supply disruptions. Plants can share responsibilities effectively, diversify their energy loss and CO_2 removal deficit better through collaboration when it comes to sourcing electricity and CO_2 from external providers.

Table 5: Compensation allocated to each plant, energy and CO_2 sourced from external providers.

Plant	Compensation Received ($ k)	Shapley Value (%)	Net Compensation ($ k)	CO_2 (t)	Electricity (MWh)
[A]	72.6	27.0	2.0	543	653
[C]	68.5	25.5	3.6	778	474
[S]	127.5	47.5	25.9	523	1057
Total	268.6	100.0	31.5	1,844	2,184

5. Conclusion

This study presents a cooperative game theory approach based on the Shapley value to ensure fair distribution of resources (i.e., monetary compensation, energy supply, and CO_2 management) among plants sharing a common energy system and CO_2 capture infrastructure during operational disruptions. A case study involving a gas turbine failure illustrates how different coalition arrangements can influence how the energy reduction is managed and how compensation is allocated. Results indicate that the iron and steel plant receive the highest compensation, while the ammonia plant receive the least. In terms of energy loss distribution, the cement plant accounts for 21.7 %, followed by the ammonia plant at 29.9 %, and the iron and steel plant at 48.4 %. For CO_2, the trend is reversed, with cement plant bearing 42.2 %, ammonia 29.5 %, and iron and steel 28.4 %. The allocation results in the highest overall satisfaction for the plants based on the compensation they receive. This method provides a rational basis for fair resource allocation and enhances the robustness of industrial clusters during supply interruptions. In practice, these shares will be based on contractual stipulations; the method developed here can provide a rational and defensible starting point for negotiations. Future research should explore how various equipment failures such as steam turbine and gas engine, would affect the distribution of resources for each plant involved.

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