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RESEARCH ARTICLE

Exploring the emergence of waste recovery and exchange in industrial clusters

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Abstract

Self-organized industrial symbiosis (IS) starts with one actor's decision to invest in a waste recovery plant and the other actors' decision to buy the recovered flow. Technical and institutional conditions of the cluster influence actors' decisions. This paper explores the emergence of IS collaborations in industrial clusters under different techno-economic conditions in the long term. We propose a mixed-integer linear programming model that incorporates costs and constraints associated with waste recovery and exchange to study actors' investment decisions and investigate shaped symbiotic exchanges under rising energy prices and limited electricity supply. The approach is implemented in Iran's Persian Gulf Mining and Metals Special Economic Zone as a case study. The results revealed that changes in internal or external condition simultaneously influence the industrial and waste recovery plants. For instance, increasing energy prices without raising product prices significantly decreased the production level of industrial plants and, consequently, heat recovery potential. Furthermore, the waste heat recovery plants' contribution to improving the cluster's economic and environmental performance was not the same. Electricity recovery from a power plant's waste heat can result in 55 PJ grid electricity intake reduction and 720 M€ cluster cash flow increase. Recovered cooling or electricity from the steelmaking plant waste heat was consumed internally rather than shaping IS. These model outcomes show its capability to study IS within the socio-technical structure of the cluster, not a standalone phenomenon. Implemented conceptualization offers a novel system-level approach, which could be adjusted to assess other industrial development strategies.

KEYWORDS
carbon emissions, complex industrial systems, industrial ecology, industrial symbiosis, MILP model, techno-economic analysis

1 | INTRODUCTION

Industrial clusters are complex systems of actors that benefit from clustering in many ways, including the waste material and energy exchange, known as industrial symbiosis (IS). IS implementation in industrial clusters requires a dynamic interdisciplinary approach to understand how various internal and external conditions influence the emergence of symbiotic collaborations (Boons et al., 2014; Yu et al., 2014). Generally, waste flows need treatment, referred to as waste recovery, before exchange between two actors (Fraccascia et al., 2017a). Several waste recovery options with different techno-economic specifications might be technically possible in a cluster. Actors decide on waste recovery based on the economic benefit, motives, previous collaborations, and institutions governing those collaborations (Albino et al., 2016; Fraccascia et al., 2017b; Noori et al., 2020; Spekkink & Boons, 2016). Governments can also foster IS through pricing, regulatory enforcement, and infrastructure provision (Fraccascia et al., 2017b; Sun et al., 2017; Yu et al., 2015). All these circumstances turn decision-making for IS into a complex multi-objective challenge.

Interestingly, while IS usually imposes additional investment and operation costs to the system, only a few models have included those costs in their formulation. The government, industries, or a facilitating body can make the required capital investments at the system level. Taskhiri et al. (2015) developed a formulation to maximize the satisfaction level of actors based on the investment payback period in a waste-to-energy network. While their model considered the investment cost and its allocation among the actors, it ignored the time value of money in the investment decision. Teo et al. (2017) developed a hybrid optimization model to integrate a sustainable central utility system into an eco-industrial park. They evaluated the system's economic performance based on net present value but overlooked the role of social drivers in decision-making. We argue that it is crucial to correctly incorporate operation and investment costs in the model to investigate actors' decisions.

Modeling is a standard method for the structured investigation of complex systems (Greiner et al., 2014). Different modeling approaches have been used to study IS formation depending on the problem formulation and the modeling question. One approach is agent-based modeling (ABM), where the actors' status and interactions are simulated in a descriptive bottom-up approach to gain insight into the emergent behavior of a system (Ghali et al., 2017). A drawback of ABM is its incapability to optimize the economic benefit of actors (Davis et al., 2009), which plays an undeniable role in IS formation. Another widely used modeling approach is linear programming and optimization. Montemanni and Jamal (2018), for instance, presented a model to maximize the cash flow of a whole industrial cluster. Although they defined cluster prices for each by-product, the model did not include waste recovery costs.

Most optimization models have targeted economic benefits, but increasingly multi-objective models include environmental or social aspects of IS in the optimization process. For instance, Afshari et al. (2018) incorporated environmental impact in their objective function to optimize a heat exchanger network in eco-industrial parks, while Brondi et al. (2018) coupled life cycle sustainability assessment in a symbiotic network optimization under different scenarios. An interval chance-constraint fuzzy program including environmental limitations (Rao et al., 2019) and a pricing model for waste recovery (He et al., 2020) are other recent efforts to develop more inclusive optimization models for assessing IS.

Investments in waste recovery are a long-term decision for industrial actors. But, industrial clusters are not static systems and change over time due to internal and external conditions' variations. Regulations and policies such as waste transportation cost (Domenech et al., 2019), taxes (Fraccascia et al., 2017b), environmental limitations (Yu et al., 2015), governmental stimulation plans (Behera et al., 2012), and infrastructure readiness (Sun et al., 2017) are external parameters that influence actor's decision-making. Moreover, previous successful collaborations (Spekkink & Boons, 2016) and actors' motivation to engage in IS also impact the system internally. Internal and external parameters influence multi-criteria decisions for waste recovery and exchange. A way of understanding the impact of uncertainties in future developments is scenario analysis (Enserink et al., 2010). Scenario analysis explores a range of plausible future outcomes of a system and investigates development paths resulting in such futures.

Based upon and related to the points discussed above, this paper explores which IS collaborations could emerge in industrial clusters in the long term under different technical and institutional arrangements. We built a socio-technical cluster model using a case study of the Persian Gulf Mining and Metal Industries Special Economic Zone (PGSEZ) in Iran. This model examines different waste recovery options under increasing energy price and limited energy supply scenarios, although the proposed conceptualization is not limited to these external factors. The model is built in Linny-R, a graphical user interphase for mixed-integer linear programming problems developed at the Delft University of Technology (Bots, 2021). It uses Gurobi mathematical optimization solver (Gurobi Optimization, 2021). A brief introduction to Linny-R and its implication in IS modeling is given in the Supporting Information. Linny-R provides the possibility to include physical and non-physical processes and flows in one model and to find the cheapest way of meeting the demands regarding technical and non-technical constraints.

This paper is divided into five sections. Section 2 explains Linny-R's methodological background, IS conceptualization, and modeling. In Section 3, the model is applied to a case study. The results are presented in Section 4. Finally, discussions and contribution of this work to IS modeling studies is stated in Section 5.

2 | METHODS

2.1 | Modeling industrial systems in Linny-R

In this paper, we implemented Linny-R modeling tool for techno-economic analysis and optimization of industrial systems. The building blocks of a Linny-R model are "Products" and "Processes." A product represents something that can be produced or consumed by a process, either tangible

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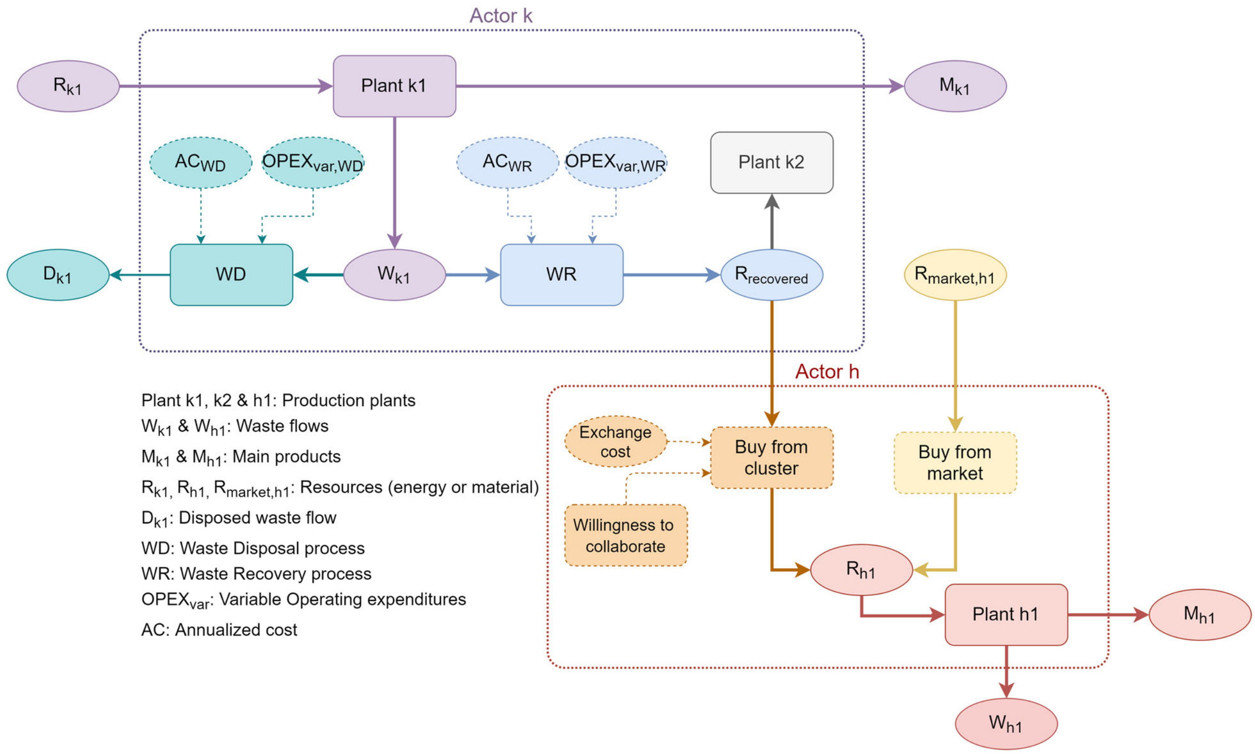

FIGURE 1 Conceptualizing waste recovery and exchange between two actors based on Linny-R

(e.g., material and energy) or intangible (e.g., information, money). A process is an activity owned by an actor that transforms some products into others (Bots, 2021). A process could also be physical (e.g., an industrial plant) or non-physical (e.g., investment, selling). Processes and products are constrained by their upper and lower bounds and connected through links. Non-physical entities (called data-type entities) enable the modeler to implement economic, environmental, and institutional costs and restrictions to the model. Linny-R also accepts time series, data sets, or functions as input parameters with temporal changes. Continuous variables of the Linny-R optimization function are production levels of processes, and integer variables are the start-ups of new processes. Linny-R maximizes profit or minimizes the cost of the entire system subject to constraints applied to products, processes, and links between them.

2.2 | Conceptual model for waste recovery and exchange

Figure 1 conceptualizes waste recovery and exchange between two actors, *k* and *h*, in which rectangles and ovals illustrate processes and products, respectively. Dotted shapes represent data-type entities. Plant *k1* consumes resources R_{k1} to generate main product M_{k1}, while waste product W_{k1} is also generated. Two routes are possible for W_{k1}: sent to waste disposal (WD) or waste recovery (WR). Each route might incorporate operation or investment costs shown by OPEX (Operating Expense) and AC (Annualized Co). If sent to WR, recovered flow ($R_{recovered}$) could either be utilized internally by the actor (e.g., in plant *k2*) or traded with actor *h*. Actor *h* has two options to meet resource requirements for plant *h1*: buy from the market or buy from actor *k*, which might incorporate some exchange cost. The actors seek the cheapest way to operate, considering system conditions. Moreover, the actors willing to collaborate could influence this decision. IS shapes when actor *k* selects waste recovery over waste disposal, and actor *h* decides to buy from actor *k* instead of the market.

2.3 | Applying IS costs and constraints to the conceptual model

Several costs and limitations are associated with processes and products shown in Figure 1 and influence IS formation. The upper and lower bounds of processes, either physical or non-physical, represent their minimum and maximum capacity, and inflow and outflow rates equal resource consumption and product/ by-product generation rates. A negative product level means its extraction as a source, and setting a negative lower bound reflects the maximum available amount of the source. A positive product level shows its generation, and a positive upper bound is used to set the maximum demand for that product. A price must be assigned to every product; otherwise, it will be assumed zero while solving the optimization problem. Tax on a product could be implemented as a negative price. As explained in Section 2.1, all these parameters could change over time in the form of time series, functions, or data sets. Other parameters are described in more detail as follows.

2.3.1 | Operation and investment costs

Operating an existing process or establishing a new process might impose capital expenditures (CAPEX) or OPEX on the actor. Variable OPEX, which is proportionate to the production level of the process CAPEX, could be applied to the process as an input product. Fixed costs (CAPEX and fixed OPEX) are reflected in annualized cost (AC) (Equations 1 and 2). As a start-up cost, AC will be deducted from the actor's cash flow annually when the process comes into operation, regardless of its production level.

$$\mathrm{CRF} = \frac{R}{1-(1+R)^{-n}} \tag{1}$$

$$\mathrm{AC} = \left(\mathrm{CAPEX}\cdot \mathrm{LF}_{\mathrm{cap}}\cdot \mathrm{CRF}\right) + \left(\mathrm{OPEX}_{\mathrm{fixed}}\cdot \mathrm{LF}_{\mathrm{op}}\right) \tag{2}$$

Where:
R: interest rate
n: the repayment period
$\mathrm{OPEX}_{\mathrm{fixed}}$: fixed operation expenses
$\mathrm{LF}_{\mathrm{cap}}$: CAPEX location factor (material cost factor × contingency factor)
$\mathrm{LF}_{\mathrm{op}}$: labor cost location factor (labor productivity factor × labor cost factor)

2.3.2 | Exchange costs

Exchanging a recovered flow between two actors entails the costs of contracting or establishing a new connection. This cost could be assigned to each buying process as a start-up cost and deducted from the buyer's cash flow as soon as the exchange occurs.

2.3.3 | Willingness to collaborate

Non-economic considerations might influence actors' decision to exchange recovered flow, called in Figure 1 as "willingness to collaborate." It is possible in Linny-R to constrain one process's operation to another. Therefore, the "buy from cluster" process comes into operation if the level of willingness to collaborate is higher than a defined amount. However, willingness to collaborate is an exogenous parameter of the model and must be assessed through separate studies. For instance, the literature shows that actors engaged in pre-emergence collaborations and open to new businesses are more likely to start symbiotic exchanges (Ashton & Bain, 2012; Spekkink & Boons, 2016).

2.4 | Model formulation

As stated in Section 2.1, Linny-R maximizes the cash flow of the system (or selected actors) subject to conditions applied to products, processes, and their links. In an industrial cluster, each actor might hold several processes. The cash flow of actor k, U_k, is the sum of the A_k's profits from all processes owned by A_k:

$$U_k = \sum_i \mathrm{CF}_i \tag{3}$$

where, CF_i is cash flow of process i owned by actor k. Process cash flow equals income from outgoing products minus its expenditures. The expenditures are the total cost of input products, plus the operation and investment costs. Therefore, the cash flow of a representative process i can be formulated at each time step as:

$$\mathrm{CF}_i = \mathrm{PL}_i \cdot \sum_m Pr_m \cdot O_{i,m} - \mathrm{PL}_i \cdot \sum_n Pr_n \cdot R_{i,n} - \mathrm{PL}_i \cdot \mathrm{VC}_i - \mathrm{AC}_i \tag{4}$$

TABLE 1 Companies and production plants in PGSEZ

Company	Plant	Type (*)	Capacity
Kish South Kaveh Steel Company (SKS) (sksco.ir/)	P1	DRP	1,850,000 t/year
	P2	SMP	1,200,000 t/year
Hormozgan Steel Complex (HOS) (hosco.ir/)	P3	DRP	1,650,000 t/year
	P4	SMP	1,500,000 t/year
	P5	CBP	75,000 t/year
Hormoz Power Plant (HPP) (pgsez.ir/)	P6	GPP	160 MW
Persian Gulf Saba Steel Company (SAB) (sabasteel.co)	P7	DRP	1,000,000 t/year
Almahdi Aluminium Complex (AAC) (almahdi.ir/)	P8	ABP	93,000 t/year
	P9	ARP	172,000 t/year

*DRP: Midrex Direct Reduction Plant, SMP: EAF Steelmaking Plant, CBP: Cold Briquetting Plant, GPP: Gas turbine power plant, ARP: Hall-Héroult Aluminium Refining Plant, ABP: Anode Baking Plant.

Where:

PL_i: Production-level process i

Pr_m: Price of product m

$O_{i,m}$: Generation rate of output m of the process i to produce one unit of the main product

$R_{i,n}$: Consumption rate of resource n to produce one unit of the main product

VC_i: Variable cost process i for a unit of main product

AC_i: Annualized cost process i

The formulation applies to each process owned by an actor. If an actor decides to start a process under specific circumstances, the variable in the formula is multiplied by a binary variable to express such a decision. Therefore, the optimization model is defined by Equation (5), in which the decision variables are production levels and process start-up integer variables.

$$\text{Optimize} \sum U_k \tag{5}$$

Subject to the constraints elaborated in Section 2.3

3 | THE CASE STUDY

A case study was used to explore how energy availability and price changes can influence IS formation in an emerging industrial cluster. The PGSEZ in Iran was selected. PGSEZ was established near South Pars natural gas fields to exploit the comparative advantage of extensive energy resources in developing energy-intensive industries. A previous survey showed that successful pre-emergence collaborations in this cluster were self-organized mostly (Noori et al., 2020). Moreover, IS is not referred to directly in Iranian rules and regulations. Rules and regulations primarily define obligations for industrial actors to improve their energy and environmental performance. Responsibilities of the government or cluster management, for example, in facilitating or financing such improvements, are vague and limited. A detailed institutional study showed that rules and regulations in Iran also support self-organized IS (Noori et al., 2020). Table 1 shows the companies and plants included in the case study. For modeling purposes, the maximum capacity of the plants was considered equal to the design capacity. Industrial water was assumed as an input into the processes to decrease complexity.

Each company was modeled as a sub-cluster that includes all related processes and products. Waste streams were considered to have no economic value for the actors. Each time step in the model was considered a year, and the system was then simulated for 20 years.

Increasing electricity demand by conventional air conditioners in the household sector has caused electricity shortages in Iran (Azadi et al., 2017). Thus, the possibility of supplying recovered electricity to Bandar Abbas city (BAC), at a 14-km distance from PGSEZ, was added to the model. Electricity demand for cooling was assumed to be one third of household electricity consumption (Pourazarm & Cooray, 2013) and increased at the same rate as urban population growth. To take into account the differences in prices, urban and industrial electricity were modeled separately.

3.1 | Input data

As described in Section 2.2 and in the Supporting Information, all incoming and outgoing flows of different industrial plants are required to model the cluster for IS examination. However, Linny-R does not conduct process mass and energy balances itself. All incoming and outgoing flow rates explained in Section 2.3 were obtained from a previous technical study (Noori et al., 2021) (Supporting Information).

All flows were priced based on the literature or publicly available data. See the Supporting Information for costs and prices used in this study. Because Iran's economy has been highly affected by sanctions and the US withdrawal from the Joint Comprehensive Plan of Action in 2018, the model was therefore built based on economic data for the year 2016 to exclude distortion in prices. Household and industrial electricity prices were obtained from Iran's power generation and distribution company databases (Noori, 2020b). A previous institutional study showed no explicit penalties or limitations for waste disposal applied in PGSEZ (Noori et al., 2020). Therefore waste disposal cost was set equal to zero in the model.

A previous collaboration study revealed that three steel production companies (SKS, HOS, and SAB) had experienced more collaborations with each other, so they were more willing to collaborate. In contrast, the power plant (HPP) and aluminum reduction company (AAC) had rarely collaborated with the others (Noori et al., 2020). Although the actor's willingness to collaborate can be incorporated in the model as explained in Section 2.3.3, we explored all techno-economically feasible IS connections without implementing such a limitation. Then, the results were interpreted considering involved actors' previous collaborations.

3.2 | Model verification

As the model explores future development under different configurations and scenarios, it was not possible to compare the outcomes with actual data. However, model functionality can be examined by looking at the current cluster structure and model outcomes under extreme boundary conditions. First, it was checked whether the model could replicate the present exchanges in the cluster. When adding the possible connections between these two actors, the model results showed 195,000 tones/year surplus sponge iron and 21,000 tones/year of dust oxide flow from SKS to HOS. A further look into actor cash flows showed that these trades increased HOS and SKS cash flows by 6% and 15%, respectively. The economic viability of these options is in agreement with the current existing collaboration in PGSEZ, as was observed in a previous field study (Noori, 2020a). The model was also run for extreme boundary conditions. For instance, as expected, the industrial plants stopped the operation because of increasing raw material prices or decreasing market prices. Furthermore, the model was checked at every development step for any unreasonable outcome, such as negative cash flows or sharp fluctuations in flow rates. Although these tests do not constitute a complete verification of the model, they provide confidence in the robustness of the results.

3.3 | Experimental design

3.3.1 | Configurations

A previous technical potential study revealed several unutilized IS possibilities in PGSEZ (Noori et al., 2021), three of which were examined in this paper, focusing on energy flows. We modeled four cluster configurations with different waste recovery and exchange opportunities. Configuration A represents the existing structure of PGSEZ with no IS, while Figure 2 illustrates the other three configurations. In configuration B, waste heat from the power plant (WH_{P6}) is recovered in P14. Recovered electricity could be consumed by SKS, HOS, SAB, AAC, the urban area (BAC), or sold to the grid.

As SKS has previously had several successful collaborations with other actors in the cluster (Noori et al., 2020), configurations C and D explored its potential for IS collaborations. In configuration C, cooling recovery from steelmaking plant waste heat (WH_{P2}) was added to the model. WH_{P2} has a temperature of 90°C, which is suitable for cooling recovery through an absorption chiller (P16) (Oluleye et al., 2017). Detailed inspection of cluster cooling demands (Supporting Information) revealed that generated cold water in P16 could be utilized in SKS or HOS instead of their existing evaporative cooling tower system. In configuration D, energy recovery from WH_{P2} before internal cooling was examined. The 15–35% of energy input to electric arc furnaces (EAF) is lost through off-gas (Barati, 2010; Kirschen et al., 2011; Steinparzer et al., 2014). Several studies have investigated energy recovery from this flow, though only a few have been implemented at an industrial scale. Here, we considered a waste heat steam generator plus an ORC (P18) to recover electricity from steelmaking plant waste heat. Recovered electricity can be used internally, exchanged with HOS, SAB, AAC, or BAC, or sent to the grid.

WR efficiencies were obtained from the literature. In the case study, we assumed that existing production plants had been paid off completely. Thus, CAPEX was applied only to P14, P16, and P18. CAPEX and OPEX were obtained from the literature and adjusted to the case study conditions using location factors. An interest rate of 10% and a repayment period of 20 years were considered for the CRF calculation (Equation 1). AC was calculated as explained in Section 2.3.1, and the cost price of recovered flow was obtained by dividing AC by WR capacity and adding variable cost to it. Technical specifications were considered stable during the simulation. The Linny-R models of the four configurations and assumptions on other economic parameters used in the models are summarized in the Supporting Information.

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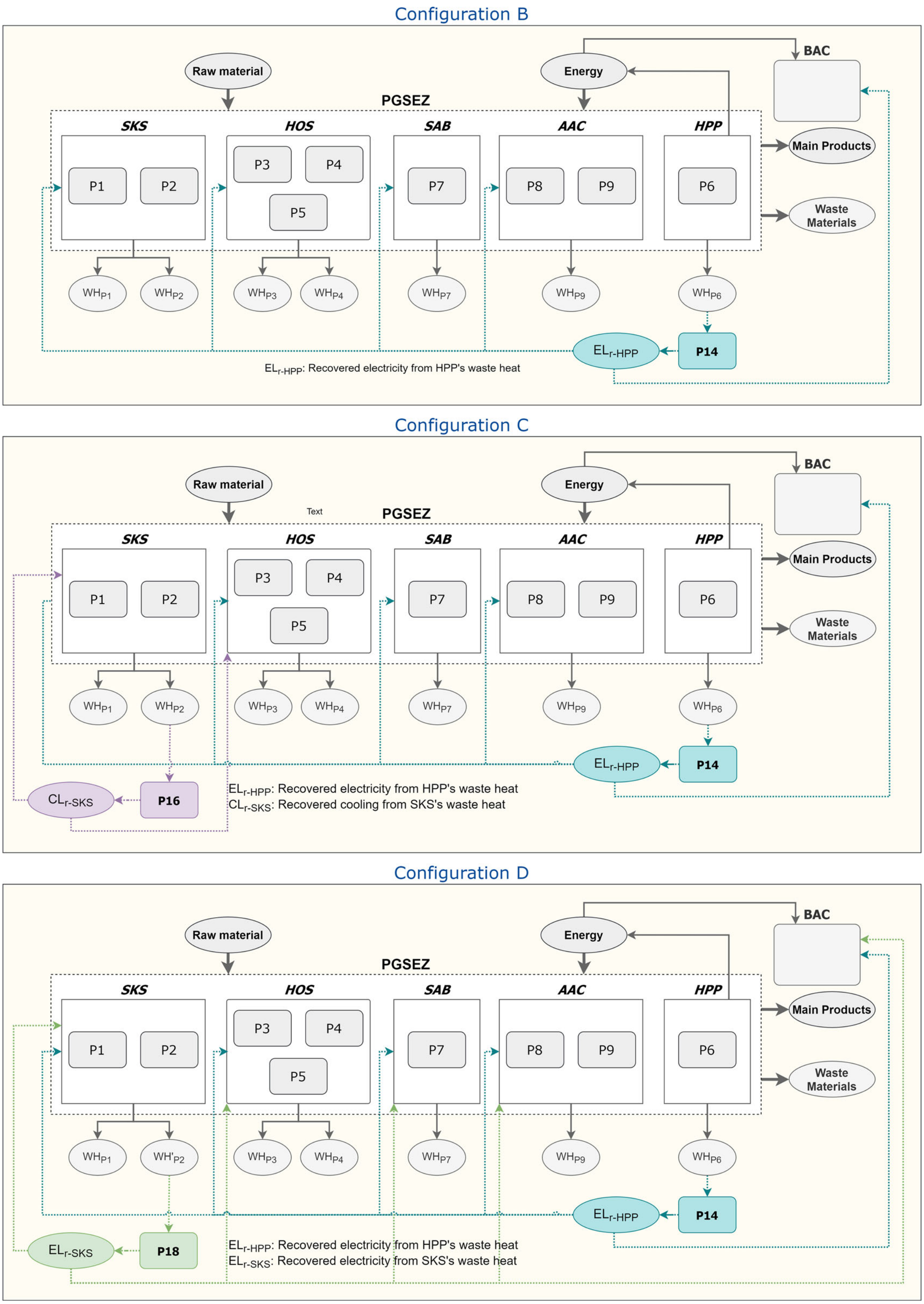

FIGURE 2 Waste recovery and exchanges in configurations B, C, and D

3.3.2 | Scenarios

In this step, we investigated how variation over time in external factors influences the formation of IS in PGSEZ. More specifically, we examined the role of energy prices and resource availability. The current energy sources of PGSEZ are natural gas and electricity. In Iran, electricity and natural gas prices are not set through a market mechanism but are determined by governmental legislation annually. Current energy prices in Iran

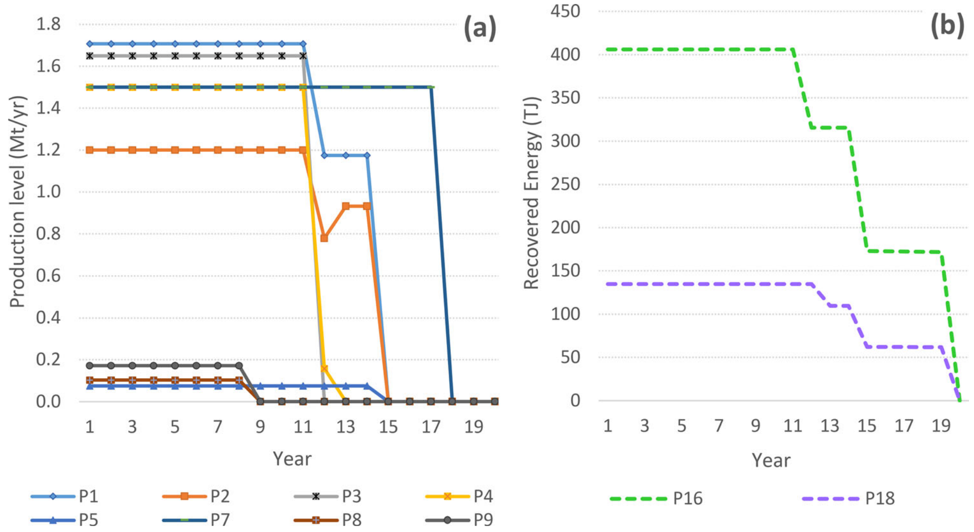

FIGURE 3 Production levels in EN+RA0 scenario: (a) industrial plants and (b) waste recovery plants. The underlying data for this figure can be found in Supporting Information S2.

are significantly lower than EU average prices and have not increased dramatically during the last years (Noori et al., 2020). Energy prices were changed under three scenarios to study the impact of institutional conditions on IS emergence. In the EN0 scenario, energy prices remained fixed during the next 20 years. In the moderate rise scheme (EN+), prices increased yearly by 10%. In a drastic rise scenario (EN*), the prices were first doubled and then increased by 10% annually.

In a previous field study in PGSEZ, actors pointed out limited electricity supply from the grid as a prominent driver for IS (Noori, 2020a). We designed another set of scenarios to examine the effect of this limitation on IS. RA0 presented unlimited electricity availability, while in RA-, the maximum electricity supply from the grid was equal to 50% of cluster electricity consumption in the current condition. Combining external factor variations resulted in a total of six scenarios in this study namely, EN0RA0, EN+RA0, EN*RA0, EN0RA-, EN+RA-, and EN*RA-.

4 | RESULTS

Only selected model outputs are presented in this section. The detailed excel sheets of model results in different configurations and scenarios are provided in the Supporting Information.

4.1 | Operation of production and waste recovery plants

Before exploring symbiotic exchanges, we investigated the operation of production plants and waste recovery plants. Investigating production levels of industrial plants in configuration A showed that energy price and resource scarcity did not affect all plants in the same way. The grid's limited electricity supply forced the aluminum processing plants (P8 and P9) to stop, but the production level of other plants did not change in RA- scenarios compared to RA0.

The power plant (P6) operated at maximum capacity in all scenarios. Other plants also operated at full capacity in EN0RA0 but shut down one by one at a moderate annual rise in energy prices (Figure 3a). P9 and P8, the most energy-intensive plants in the cluster, stopped operation in the ninth year when electricity and natural gas prices reached 9.5 and 1.8€/GJ, respectively. P3 and P4 (DRP and SMP of HOS) stopped production afterward. However, P5 (CBP of HOS) stayed in operation until the year 14, receiving iron dust from SKS. P1 and P2 (DRP and SMP of SKS) operated until energy prices were almost 3.5 times higher than current prices. P7, the less energy-intensive company in the cluster, operated until year 17. A similar shutdown sequence was observed in EN* at the same energy prices, which happened sooner in this scenario.

Except HPP, actors' cash flow dropped by EN+ scenario and even more in EN*. The highest drop happened for HOS. Under constant energy prices, HOS and SKS had higher cumulative cash flows, but the cash flow of SAB surpassed HOS and SKS in EN+ and EN* scenarios. Note that the cash flow of the urban area (BAC) was negative, as it is only a consumer. As RA- influenced the production level of AAC, only its cash flow dropped in RA- scenarios.

Then we investigated production level of waste recovery plants. In configuration B, P14 operated at maximum capacity in all scenarios recovered 54.8 PJ electricity over 20 years. P14 remained in operation at full capacity in configurations C and D as well, but P16 and P18 did not (Figure 3b).

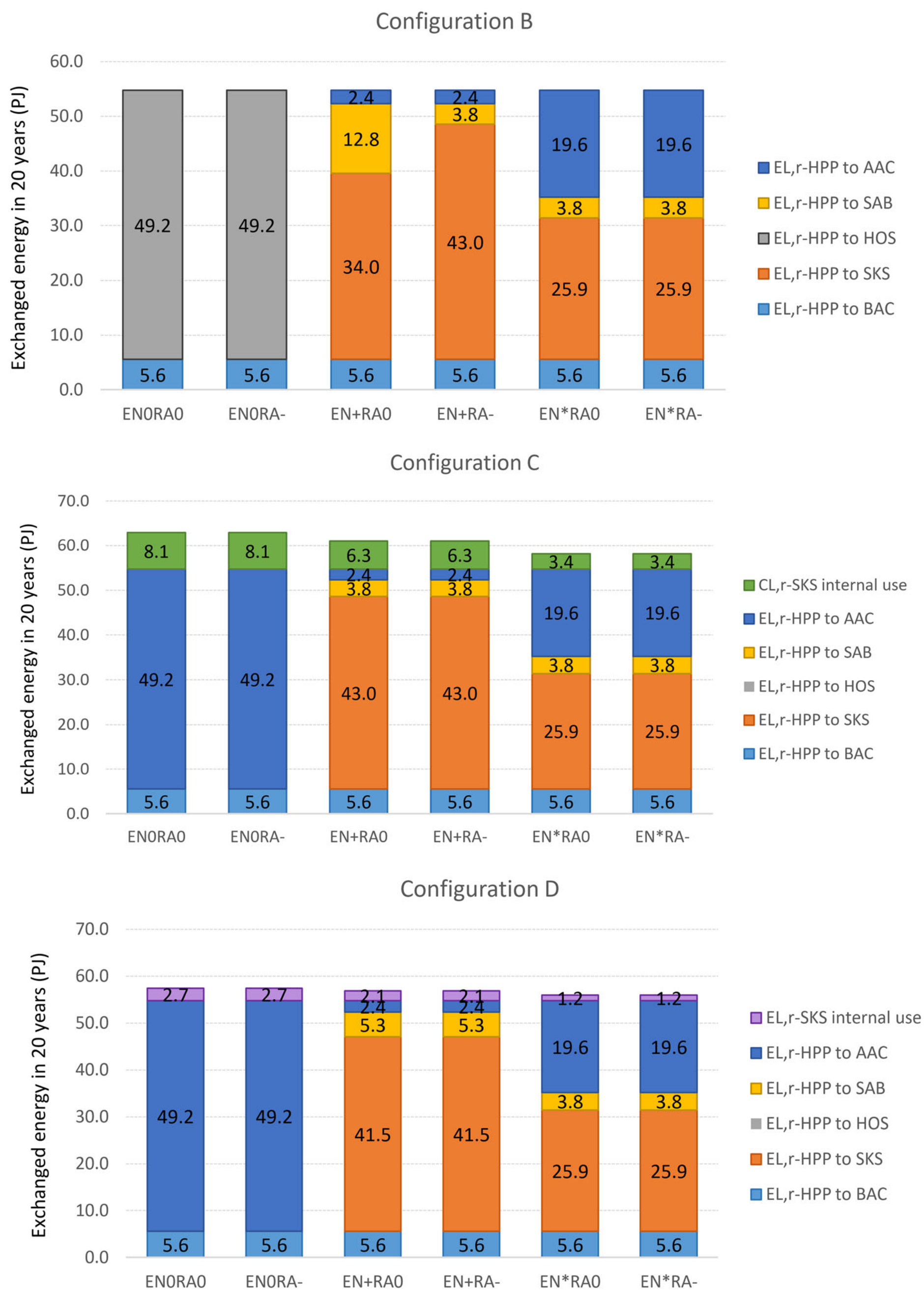

FIGURE 4 Exchanged energy among actors in 20 years in configurations B, C, and D. The underlying data for this figure can be found in Supporting Information S2.

As described above, the production level of P2, and consequently the amount of generated waste heat, dropped under a moderate and drastic rise in energy prices; but it was not influenced by resource scarcity. The same pattern was observed in the production level of P16 and P18. Under fixed energy prices, P16 and P18 could recover 8.2 PJ cooling or 2.7 PJ electricity over 20 years. In the EN+ scenario, the amount of recovered energy in P16 and P18 dropped over time and ended at zero in year 19. In EN* scenario, P16 and P18 stopped operation after the upstream industrial plant (P2) stopped operating in the 12th year at electricity price of 25.4€/TJ. These results clearly show the dependency of energy recovery on industrial plants' operations.

4.2 | Symbiotic and non-symbiotic exchanges

Figure 4 shows the utilization of recovered energy inside and outside PGSEZ over 20 years. In configuration B, 54.8 PJ recovered electricity in P14 ($EL_{r\text{-}HPP}$) was consumed by different actors under different scenarios. As the household electricity price was much higher than $EL_{r\text{-}HPP}$, the urban

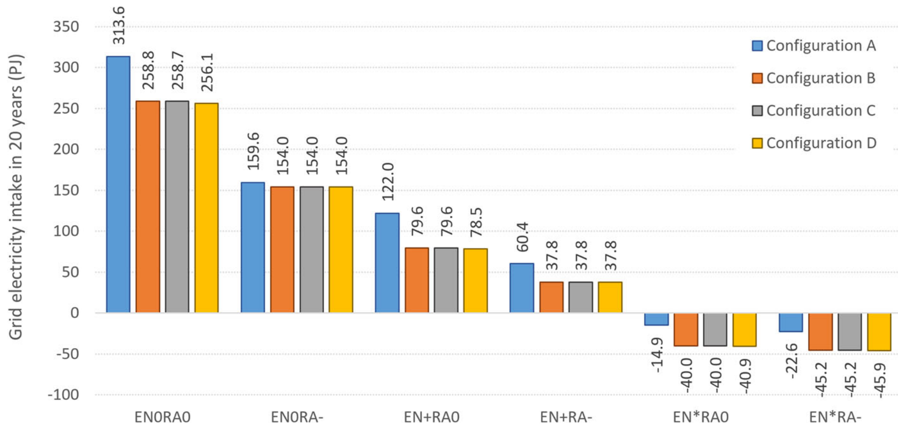

FIGURE 5 Electricity intake from the grid in 20 years under different configurations and scenarios. The underlying data for this figure can be found in Supporting Information S2.

area (BAC) received 5.6 PJ of $EL_{r\text{-}HPP}$ over 20 years in all scenarios. In the EN0 scenarios, HOS used the remaining 49.2 PJ $EL_{r\text{-}HPP}$. Under the EN+ scenario, $EL_{r\text{-}HPP}$ found new destinations, and symbiotic exchanges formed with SKS, SAB, and AAC. Electricity intake by SKS was higher than SAB because of the demand for steelmaking (P2). AAC also received 2.4 PJ in the last year. When grid electricity prices increased drastically, symbiotic exchanges helped AAC to start production again from year 13, consuming annually around 2.4 PJ $EL_{r\text{-}HPP}$. Thus, the share of AAC from recovered electricity increased to 19.6 PJ in EN* scenarios.

In configuration C, two waste recovery plants operated in PGSEZ simultaneously: P14 and P16. Recovered cooling in P16 ($CL_{r\text{-}SKS}$) was used internally and did not result in IS collaboration. However, $CL_{r\text{-}SKS}$ did not meet process demands completely, and the existing cooling system remained in operation. This change influenced the distribution of $EL_{r\text{-}HPP}$. Again, BAC received all its electricity requirements from $EL_{r\text{-}HPP}$. In EN0 scenarios, AAC received the remaining $EL_{r\text{-}HPP}$. In EN+RA0, the share of SKS from $EL_{r\text{-}HPP}$ increased compared to the same scenario in configuration B. In the other three scenarios, $EL_{r\text{-}HPP}$ was used the same way as configuration B. We replaced P16 with an electricity recovery unit (P18) in configuration D. Although P18 came into operation in all scenarios, partially or entirely, all recovered electricity was consumed internally in SKS and did not result in IS. $EL_{r\text{-}HPP}$ utilization pattern remained almost similar to configuration C.

In all these configurations, energy recovery in HPP played a significant role in the prospected IS collaboration. However, a previous study (Noori et al., 2020) showed that HPP had no substantial collaborations with the other companies in PGSEZ. The same survey showed that SKS has collaborated with other companies in the industrial cluster and expressed openness to engage in new collaborations. Nonetheless, the model showed that adding waste recovery units to SKS in configurations C and D did not result in symbiotic exchanges, although it improved the energy efficiency of SKS. These results reveal that technically feasible collaborations do not necessarily correlate with actors' historical collaborations. Historical collaboration is an important parameter but does not necessarily result in IS emergence.

4.3 | IS contribution to cluster performance improvement

4.3.1 | Grid electricity consumption

Net grid electricity consumption is the sum of PGSEZ and BAC's electricity intake minus excess electricity supply from PGSEZ to the grid. Negative values in Figure 5 represent net supply to the grid over 20 years. With a decline in industrial plants' production level in EN+ scenarios, electricity intake from the grid also dropped. In the EN* scenario, cluster electricity generation was larger than its demand, and thus the net intake became negative. All implemented waste recovery and exchange configurations decreased grid electricity intake compared to configuration A. The highest reduction was caused by P14, which had the highest capacity among the waste recovery plants and remained in operation under all examined conditions. In the EN0RA0 scenario, electricity recovery in P14 reduced electricity intake from the grid by 17.5% compared to configuration A. The amount of recovered energy in P16 and P18 was lower than the total electricity requirement of the cluster. Therefore, grid electricity intake barely dropped in configurations C and D, compared to B. Nevertheless, the energy recovery plants could not compensate for the restricted electricity supply from the grid in RA- scenarios. Therefore, the total cluster electricity intake dropped under RA- scenarios compared to RA0.

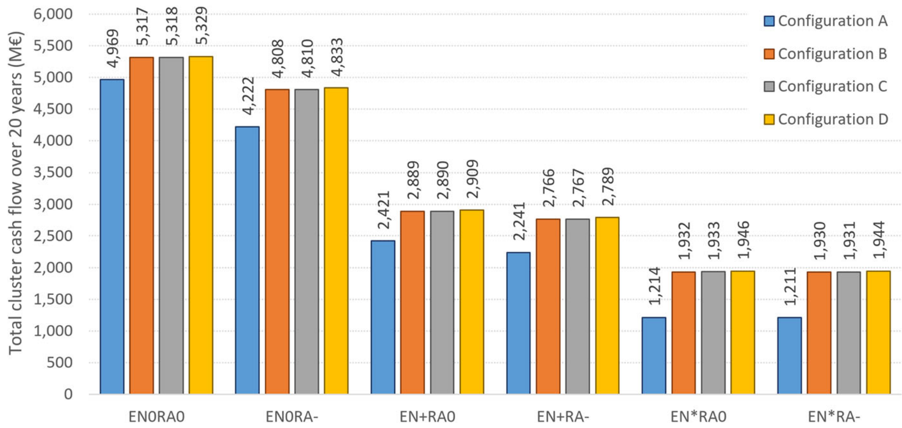

FIGURE 6 Overall cash flow over 20 years in different configurations and scenarios. The underlying data for this figure can be found in Supporting Information S2.

4.3.2 | Cluster cash flow

Figure 6 shows the 20-year cash flow of the system. In all configurations, cash flow dropped by increasing energy prices. Unless under fixed energy prices, restricted electricity supply from the grid did not influence overall cash flow significantly. Figure 6 also shows that overall cash flow increased in configurations B, C, and D investment and operation costs of waste recovery plants. However, the increase was minor in configurations C and D compared to B. Under current energy prices, investment in P14 in configuration B resulted in overall cash flow improvement by 348 M€. Under moderate and drastic rise in energy prices, cash flow improvement due to recovered energy utilization increased and reached 719 M€ in EN*RA- scenario.

4.4 | Sensitivity analysis to product prices

As discussed in Section 4.1, an increase in input energy prices decreased actors' cash flow and resulted in a reduction in the production level of industrial plants (Figure 3). Consequently, the amount of recovered waste heat declined, and the energy exchange pattern among actors changed (Figure 4). In those scenarios, we kept the market price of the final products fixed. Therefore, cash flow decreased by rising input energy prices. In this section, we provide results of the sensitivity of the results to increases in product prices. We increased the product prices by 1% to 6% annually in the six scenarios.

First, we investigated under which increased market prices the industrial plants maintained production at maximum capacity despite rising energy prices. The results were different for EN+ and EN* scenarios. In the absence of waste recovery and exchange, SKS and HOS continued production at maximum capacity with a 2% and 3% annual rise in market prices under EN+ and EN* scenarios, respectively. For SAB, the required increase rate in market price to prevent a drop in production level was 1% in the EN+ scenario and 2% in EN* scenario. The rates were 3% and 6% for AAC, respectively. Configuration B improved HOS's operation, where the required product price increment to remain operational at full capacity under the EN+ scenario was 1%. In configurations C and D, the same behavior was observed for SKS.

As stated in Section 4.1, the production level of P14 was not changed by rising energy prices. Nevertheless, P16 (in configuration C) and P18 (in configuration D) stopped operation after a few years, followed by the same trend in the production level of P2. A 1% and 3% increase in product prices under EN+ and EN* scenarios prevented the drop in the production level of P2. Consequently, P16 and P18 did not stop operation. However, again, all recovered energy was consumed by SKS internally.

The annual rise in product prices increased the cash flow of all actors. Symbiotic exchanges among actors were influenced widely by this change. For instance, in configuration B, a 1% and 2% rise in product prices turned HOS the primary receiver of $EL_{r\text{-}HPP}$. Under 3% and more product price rise, AAC started to receive the majority of $EL_{r\text{-}HPP}$. These observations matched with changes in production level observed in the above section. In configuration C, the primary receivers of $EL_{r\text{-}HPP}$ were HOS, SKS, and AAC under 1%, 2%, and 3% rise in product prices, respectively. Only recovered energy supply to BAC remained untouched in all configurations. BAC received all its 5.6 PJ electricity requirements from HPP despite all changes.

5 | DISCUSSION

This paper investigated the emergence of IS collaborations in industrial clusters under varying external conditions. It proposed a system-level approach for techno-economic analysis and exploring waste recovery and exchange configurations. The approach's novelties were decomposing symbiotic exchange into a set of physical and non-physical processes and flows, applying cluster's technical, economic, and institutional requirements as model constraints, and giving actors the opportunities to select among different waste management options. This paper's conceptualization and modeling approach does not have a complicated formulation but an easy-to-understand visual interface. As argued in the introduction, many previous IS studies have not dealt with the impact of waste recovery's investment and operation costs and the present value of this investment on actors' decisions. This paper dealt explicitly with actors' investment decisions in waste recovery in the long term while external factors change over time.

We showed that a steep rise in energy prices does not necessarily result in further waste recovery and exchange. A steep rise in energy prices results in a drop in the production level of energy-intensive plants. This drop decreases the generated waste heat and the demand for recovered energy. It also lowers actors' cash flows and influences their investment decision on waste recovery plants. Variations in energy prices also affects the utilization of recovered energy by the other actors. In our case study, although recovering the power plant's waste heat was techno-economically feasible under all examined scenarios, the primary receiver of recovered electricity changed with increasing energy prices; thus, pointing out the need to study IS formation in conjunction with the whole system operation.

Moreover, our model showed that every technically possible waste heat recovery option does not necessarily improve cluster cash flow and electricity consumption. The system analysis should include technical and economic considerations of different waste heat recovery technologies.

Comparing shaped symbiotic exchanges with previous field studies revealed that techno-economically feasible collaborations do not necessarily correlate with the network of previous collaborations. For instance, despite SKS being perceived as one of the most willing actors to engage in new collaboration in the industrial cluster, adding waste heat recovery plants to SKS did not result in IS connections. On the other hand, HPP showed substantial energy exchanges while not experiencing many previous collaborations in the cluster. However, it should be noted that although our conceptualization allows the modeler to incorporate social parameters in actors' decisions, social characteristics are exogenous parameters for economic optimization in Linny-R. The model does not replicate social parameters, but if properly assessed and quantified outside the model, social factors could be added above economic benefit as an influential factor in waste recovery and exchange.

A sensitivity analysis showed that a rise in the product prices enables energy-intensive industries to operate at maximum capacity despite increasing energy prices. Consequently, related waste recovery plants could work at full capacity. In our case study, the amount of recovered electricity by the power plant was not sensitive to changes in steel prices, but its utilization by other actors was, which shows how actors' cash flow influences their production levels and affects optimal cluster energy supply patterns.

Every model is embedded in a system of assumptions. In this paper, a key assumption was that the waste recovery process was owned by the actor who generated the waste. Other business models are indeed possible, which calls for further research. Moreover, other actors, such as facilitators, governmental organizations, or cluster management, could be introduced to model different IS dynamics. Depending on their role, the actors can contribute to waste recovery and exchange costs. If the actor is a non-profit organization, Linny-R settings could exclude it from the economic optimization procedure.

We applied a fixed connection cost to the receiving actor in the case study. However, every two actors might have different contracting and supervision costs (Fraccascia et al., 2017b) or investments required for the exchange (e.g., piping). These costs could be implemented by defining two separate sell and buy processes for two actors. Also, it should be noted that a more detailed techno-economic study is necessary before implementing this system-level assessment. Incorporating non-physical and physical entities in Linny-R provides a novel opportunity for system-level analysis of industrial clusters. This approach can be easily adjusted for any industrial cluster, while its application is not limited to IS. It provides a basis to study different industrial development strategies under various external conditions.

CONFLICT OF INTEREST

The authors declare no conflict of interest.

DATA AVAILABILITY STATEMENT

The data supporting this study's findings are openly available in 4TU.ResearchData at https://doi.org/10.4121/17886707.v1

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SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

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