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RESEARCH

A study on end of life photovoltaics as a model for developing industrial synergistic networks

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Abstract

Industrial symbiotic networks (ISNs) can support the transition from a conventional linear economy to a circular economy by using industrial waste and by-products as resources. However, the early design and development stages of ISNs are fraught with challenges as a result of limited information (supply, demand, potential synergies, etc.), and the need to consider conflicting sustainability objectives. ISN development is a combinatorial problem and can be expressed as a Multi Objective Optimization (MOO) model, the solution of which can aid practitioners in early decision-making and the identification of appropriate industrial synergistic partners. Inspired by the principles of self-organization among stakeholders to further sustainability, an ISN resulting by applying a hybrid MOO approach to tackle end of life photovoltaic (PV) modules in Arizona has been modeled. The hybrid MOO method is capable of balancing the sustainability objectives, while allocating material strategically such that resources do not get landfilled. The resulting ISN is compared with alternate ISN configurations arising from different scenarios. For instance, simply landfilling EoL PVs can result in economic losses of close to 3 million USD and a significant environmental burden (~27 thousand ton CO_2 eq). In contrast, an ISN where recovered material is consumed completely results in cost savings of 53 million USD and avoided environmental impacts of 18 thousand-ton CO_2 eq. Sensitivity analyses to account for the uncertainty related to landfilling and warehousing costs, and the distances between synergistic partners have been undertaken.

Keywords Industrial synergies · Multi objective optimization · Heuristic optimization · Hybrid optimization · Industrial ecology · Photovoltaic waste

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Introduction

Industrial symbiotic networks (ISNs) provide significant opportunities for achieving reduction in industrial waste streams and greenhouse gases, while enhancing resource conservation [37, 40]. Analogous to exchanges between actors in naturally occurring systems, ISNs function on the principle of symbiotic relationships among industrial partners as a result of exchange of industrial wastes and by-products [24, 36]. In addition to strong collaborations between regional industries, the success of an ISN depends on several factors such as knowledge of industrial waste streams, current disposal practices and potential feedstock, and an understanding of the regional economy. Demand quantities and cost-effectiveness while remaining cognizant of the environmental impacts are important additional factors. In general, the success and longevity of an ISN hinges on addressing the economic, environmental, and social pillars of sustainability concomitantly [23, 51]. An ISN may be designed as, one that is brand new or, alternatively, it could be developed as a retrofitted ISN in an industry-dense region [6, 22, 58].

Ideally, an ISN will develop as a result of synergistic associations that mitigate environmental impacts and material acquisition costs (when compared to virgin resources) [53]. However, the development of recovery and recycling infrastructure can, on occasions, exceed the cost of manufacturing a product from virgin resources, such as, solar photovoltaics (PV) [15]. This becomes evident when volumes of end of life (EoL) product remain low making it difficult to economically motivate material recovery. Nonetheless, indiscriminate disposal in the form of landfilling can be expensive because of incurred landfill tipping fees, and as a result of loss of potentially valuable materials and embedded resources. ISNs are built on the notion of industrial symbiosis (IS), and thus, by definition promote open loop recycling. Understanding the life cycle benefits by implementing efficient industrial partnerships becomes critical for an ISN, as the approach would offer multiple pathways for the utilization of recycled streams in a localized or regional economy. Given that several possible synergistic associations could arise, the identification of the optimum synergies while maintaining adequate participation (through efficient allocation) and simultaneous optimization of conflicting sustainability objectives remain challenging.

Various techniques have been investigated to identify suitable industrial synergies. In one study, a network was designed that facilitates water exchange in an ISN based on regional industrial synergies keeping in mind several possible scenarios, such as seasonal changes using the weighted-sum (WS) method [4]. Hein et al. (2015) employed the use of Design Structure Matrices (DSM) to find industrial symbiosis opportunities and subsequently used genetic algorithms to evaluate the performance of the Kalundborg eco-industrial park (EIP) [25]. It should be noted that per literature EIPs are a special case of ISNs, i.e., a network of synergies between co-located partners. Karlsson and Wolf (2008) used an optimization model to evaluate the economic benefits of industrial symbiosis in the forest industry using mixed integer linear programming (MILP) [31]. Gu et al. (2013) recognized the need to model material and energy flow exchanges and provided a generalized theoretical optimization model for material exchanges [22]. In contrast, Cao et al. (2009) used agent-based modeling and optimization on a hypothetical EIP to understand industrial symbiotic behavior and concluded that IS can greatly reduce raw material consumption and waste [8]. Hu et al. (2020) reported an empirical study for optimizing a wastewater system within an EIP for the specific purpose of reusing organic food waste as a reagent to treat this industrial wastewater [27]. Interestingly, according to Boix et al. (2015), although, several studies on the exchange of water and energy have been carried out, there are limited studies on the use of multiple objective optimization (MOO) techniques in the context of ISNs [6]. The methods used to design water networks in EIPs are based on MILP, Mixed Integer Non-Linear Programming (MINPL) and nonlinear models [10, 38, 41]. Boix et al. (2012) applied the ε-constraint MOO method to the design of a water network in an EIP, and they were able to determine several reasonable solutions using careful trade-off criteria. Fuzzy optimization and game theory have also been used to address the same problem [4, 11, 12]. Other studies highlight the importance of efficient resource allocation to promote the development of ISNs [2, 6, 19, 22]. Thus, few studies have used MOO techniques in the context of incorporating the 3 pillars of sustainability (economic, environmental, and social) for ISN creation.

Recently, Mathur et al. (2020) quantified the environmental benefits and reduced resource consumption patterns (water and energy) as a result of implementing Life Cycle Symbiosis (LCS) utilizing PV waste [44]. Adoption of PVs continues to grow rapidly, and it is estimated that by 2050, 60–78 million tons of PV waste will be generated globally. In the US alone, the cumulative mass of decommissioned PV panels will be between 7.5 and 10 million tons [29, 44]. It is therefore not unreasonable to state that globally there will be a tremendous requirement for ISNs to be developed around recovered PV waste. The present work demonstrates the application of the hybrid MOO method (a combination of exact and heuristic MOO methods) to enable ISN development specifically around PV waste in Arizona, US [17].

MOO techniques can be categorized fundamentally into 2 types: exact (Weighted-Sum method, Compromise Programming, Ranking, and epsilon-constraint (ε-constraint) method), and heuristic methods (Evolutionary Algorithms such as Genetic Algorithms, Simulated Annealing, and Tabu search). Several studies do undertake a thorough analysis on the mechanics of the WS method and compare the WS method to other exact solution and even heuristic optimization methods [30, 43, 57]. For instance, Gerandinetti et al. compare the ε-constraint method with the WS method in optimizing job scheduling in the context of cloud computing, a MOO problem that balanced waiting times and number of hosts [21]. They found that the ε-constraint method performed better by providing a greater number of non-dominated solutions than the WS method. Copado-Mendez et al. demonstrate the use of an enhanced ε-constraint MOO optimization problem to plan sustainable supply chains for ethanol and hydrogen respectively [13]. Hong et al. apply the ε-constraint method in improving airline safety through better conflict resolution by minimizing the number of maneuvers an aircraft must make, and also by minimizing the number of aircrafts that need to make maneuvers in the first place while in flight [26]. The ε-constraint MOO method has been demonstrated to forecast the stock market and also applied to implementing a decision-making framework for an electricity retailer [1, 48]. Tosarkani & Amin have used it to design a wastewater system [54]. Specifically, in the domain of manufacturing, Moussavi et al., use the ε-constraint method to enhance job rotation in a seamless manner, while others use it to a flowshop problem [3, 46].

Heuristic methods include evolutionary algorithms (EAs) such as genetic algorithms (GAs) and particle swarm. Recently, researchers demonstrated the use of a modified GA on optimizing an IS system in China resulting in potential savings in energy consumption, emissions and costs [9]. Zhang et al. demonstrated the use of MOO through EAs, specifically GAs for the purpose of urban wastewater reuse to analyze the costs, supplies, demands and pollutant reduction [60]. Similarly, Dandy et al. also used GAs to optimize water distribution networks in Australia [14]. On the whole, however, the research literature has used other methods such as MILP, Analytic Hierarchy Process (AHP), Multicriteria decision analysis (MCDA), Analytical Network Process (ANP) for optimizing and evaluating systems for sustainability [20, 42, 47, 55, 56].

This paper proposes a sustainable strategy for effectively addressing renewable energy technology waste (PVs). We describe MOO as a decision-making methodology that can avert a potential high-consumables waste crisis similar to that observed for electronics waste. In doing so, we address the following identified research gaps:

1. Identify a method for early ISN development and continuous performance evaluation.
2. Demonstrate through a case study the advantages and disadvantages of this method in the application of ISN development.
3. Via scenario analyses compare the impacts of alternative synergetic combinations relative to the ISN developed using the proposed method.

The "Methods" section proposes a hybrid MOO approach to aid in the development of an ISN that balances conflicting economic and environmental objectives as a result of forming regional synergies. The "Results and discussion" section presents and discusses scenario analyses comparing various ISN designs in terms of economic and environmental dimensions relative to one another for our case study. We have summarized our findings and conclusions in the "Summary & conclusions" section.

Methods

With a view to maximize cost savings, this study is an allocation problem to material recovery pathways maximizing avoided environmental and minimizing transportation impacts. It also proposes a method that may be effective in early design decision-making, considering several combinatorial possibilities within an ISN based on a case study (EoL PV panels).

System planning and ISN participants

Our case study, which demonstrates a MOO hybrid optimization approach for ISN planning, focuses on seven different material streams that result from treatment of EoL PVs [44]. The aim is the optimal allocation of each of these recovered seven material streams across five potential consumers and a storage site (Fig. 1).

From a design perspective, the potential network structure is predefined by identifying connections and the problem is reduced to the allocation of recovered material in a manner that encourages industrial partnerships while promoting the consumption of recovered material in an environmentally and economically sustainable way. The total supply (as a result of materials recovered) is based on the projected EoL PVs generated in the year 2030. As per projections it is estimated that in 2030 EoL c-Si PV products (at present treated as waste) will range between 1,564,000 (regular-loss) and 7,360,000 (early-loss) tons globally. In the U.S., this is expected to be between 156,400 (regular-loss) and

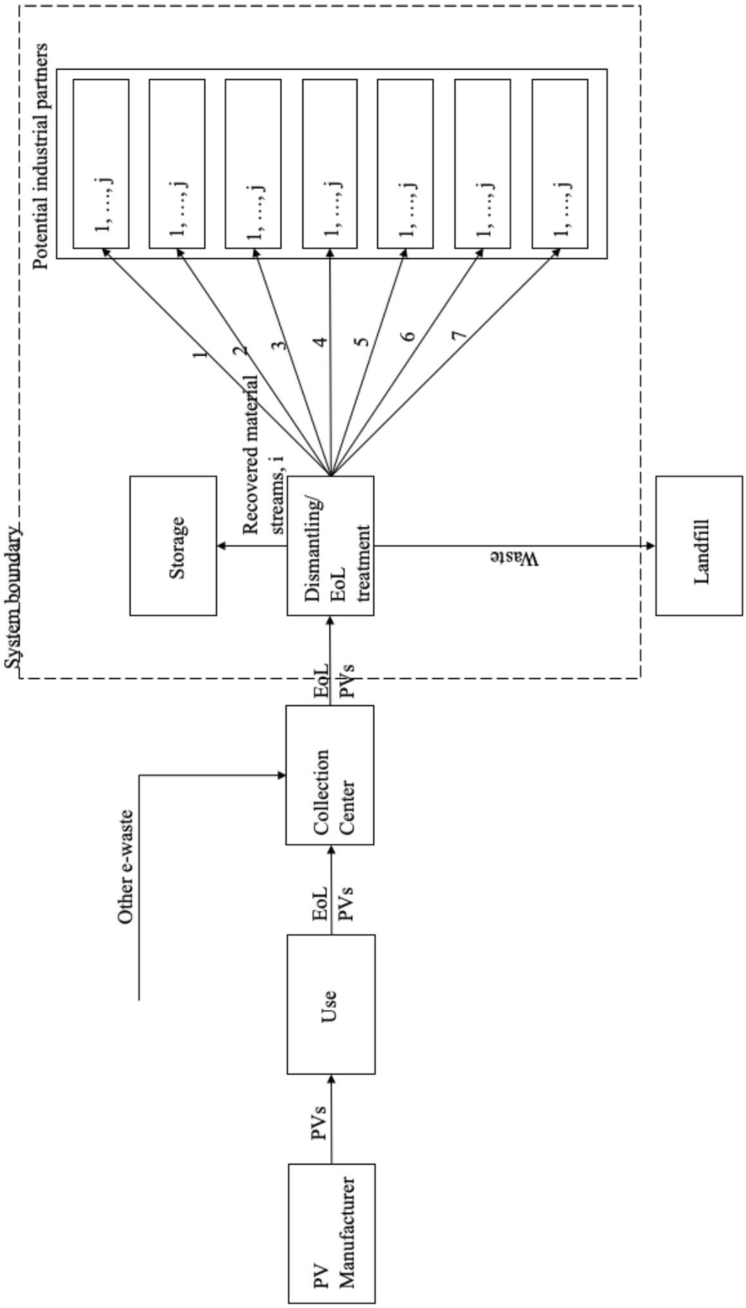


Fig. 1 ISN participants and planning

920,000 (early-loss) tons. Regular loss implies that the PV panels operate over their lifetime of approximately 30 years [28, 29, 44]. Early – loss refers to "infant, mid-life and wear-out failures" that result in a panel being retired before they fulfill their assumed lifetime [28, 29, 44].

Arizona (AZ) has approximately 5.8% of the total PV capacity of the US [49] suggesting, that by 2030, AZ will generate anywhere between 9071 tons (regular-loss) and 53,360 tons (early-loss) of c-Si PV waste. Using these values and the information on c-Si PV recovery, the quantities for each of the available material flows in 2030 to establish a PV-centric ISN in Arizona have been calculated (See S.I. 1, Table S1.1) [35, 44]. The design of the ISN is a MOO problem based on potential uses of these material streams.

Problem formulation

A MOO problem can be represented in the following mathematical form:

$$\text{Minimize, x} : f(x) = \left[f_1(x), f_2(x), \ldots .., f_k(x)\right]_K$$
$$\text{Subject to} : g_j(x) \le 0, j = 1, 2, \ldots, m$$

K is the number of objective functions and m is the number of inequality constraints.

In designing the ISN, we utilize two (K = 2) objectives; maximization of cost savings (Eq. 1), and the maximization of avoided environmental impacts (through use of recovered sources as opposed to virgin resources while taking into account transportation impacts as a result of industrial synergies) (Eq. 2, Table 1).

Table 1 Other parameters used in the proposed model

Parameter	Unit	Description
1,..i,..I	–	1,..i,..I: number of material streams isolated from EoL PVs
1,..j,..J	–	number of collaborating partners participating in the ISN
$C_{v,i}$	USD	Cost of virgin material, i
$C_{r,i}$	USD	Cost of recovered material, i
$C_{S,i}$	USD	Cost of storing material, i
C_l	USD	Cost of landfilling material
Ct	USD/km	Cost of material transport by road
X_{ai}	ton CO_2 eq	Impacts avoided as a result of recovering material, i
X_S	ton CO_2 eq	Impacts as a result of transportation to offsite warehouse for material storage
X_t	ton CO_2 eq/ ton	Transportation impacts per of material using a 32 t truck
X_l	ton CO_2 eq	Landfilling impacts
$x_{i,j}$	ton	Mass of material, i, allocated to the collaborating industries, j
$d_{i,j}$	km	Transport distance for material, i between source and collaborator, i,j
x_{is}	ton	Mass of material, i allocated specifically to the storage site, s
$D_{i,j}$	ton	Maximum demand of material i by firm j
T_i	ton	Total supply of material, i (recovered from EoL PVs)
C_{Ii}	ton	Inventory capacity for material i

Cost savings:

$$y(1) = -\left(\sum_{i=1}^{I}\left(\sum_{j=1}^{J} x_{i,j} * \left(C_{v,i} - C_{r,i}\right) + \left(x_{is} * C_s\right)\right) - \left(T_i - \sum_{j=1}^{J} x_{i,j}\right) * C_i - \left(\sum_{j=1}^{J} x_{i,j} * d_{i,j}\right) * C_t\right) \tag{1}$$

Net avoided impacts:

$$y(2) = -\left(\left(\sum_{i=1}^{I}(\sum_{j=1}^{J} x_{i,j} * X_{ai}) - (x_{is} * X_s\right) - \left(X_t * \left((\sum_{j=1}^{J} x_{i,j} * d_{i,j}\right) - \left(T_i - (\sum_{j=1}^{J} x_{i,j}\right) * X_l\right) \tag{2}$$

Both of the objectives have been expressed as minimization problems (using a negative sign), following the standard convention of optimization approaches [7]. The key decision variables to be optimized are the amounts of material flows to synergistic partners (x_{ij}) and to a storage facility (x_{is}). These need to assume meaningful levels so as to maintain adequate supply and demand while also optimizing the objective functions (Eqs. 1 and 2).

Constraints The objectives in eqs. 1 and 2 are subject to the following constraints:

a. The demand (D_i) by industries is less than or equal to the supply of recovered materials (T_i) (Eq. 3)
b. The amount of inventory that can be stored (C_{Ii}) is, at most, 5% of the amount of material supplied (T_i) (Eq. 4).

$$D_i < T_i \tag{3}$$

$$C_{Ii} \leq .05 * T_i \tag{4}$$

Assumptions In the proposed ISN, there is one source of recovered material, which is the origin of seven different material streams as a result of EoL PV recovery. For each of these 7 material streams available, five industries (per material stream) have been identified in the given region. If the supply is not entirely consumed by the industries or if the storage of material is considered more beneficial, an off-site storage facility to store a limited amount of inventory has been added. To offset the additional cost of excess inventory, we have assumed that the maximum allowable storage amount is 5% of the material supply, thus driving the material streams to be consumed promptly. In reality, storing material can mitigate supply risks (for instance due to transport delays). At this time, however, and owing to lack of data on maintaining industrial synergies for ISNs, we assume the recovered material should get consumed. This could also serve to encourage making recovery infrastructure for EoL PVs and certainly other consumables more efficient. Also, low quantities of allowable inventory of recovered materials mean lower storage costs, while fulfilling a fundamental prerequisite of a functional ISN, which is, ensuring symbiotic partnerships among and participation by industries in a given region.

This egalitarian approach with more than one consumer per material stream is inspired by the notion of self-organizing communities [50]. Disruption in supply and/or demand quantities in combination with limited partnerships can result in a brittle or less resilient ISN. We assume that the carrying cost of inventory storage is 25% of the material value [32, 52]. Material storage in the context of industrial supply and demand is not a trivial task. Several factors must be considered and the resulting costs encompass the impacts of no sales, cost of physical storage, labor, infrastructural requirements, material depreciation, etc. [32, 52]. Material that is not allocated to the industries is assigned to the landfills. The costs (C_l) and impacts (X_l) of landfilling have been accounted for in eqs. 1 and 2. Finally, we assume that a well-established infrastructure for EoL PV recovery exists, and recovered materials can be used directly as feedstock [34, 44].

Data collection

The model is based on real industry data from the greater-Phoenix region; a region of high industrial output and industrial diversity. This contributes to establishing the synergies for the proposed case study. The share of demand of the consuming firms for each material stream is modeled as industry-wise consumption shares for the estimated amount of EoL PVs generated in 2030 (S.I. 1, Table 2). Other data related to building the case study, i.e., the cost parameters, and environmental impact parameters are provided in S.I. 1. This data has been determined using reports based on commodity price forecasts [33, 45]. The cost of recovery for each material stream has been computed using economic-value allocation (S.I. 1, Table S12) [11]. Landfilling tipping fees have been obtained from literature as have the cost of carrying inventory [16, 32, 52]. Finally, avoided environmental impacts refers to the net environmental benefit of using recovered resources as opposed to virgin feedstock. These values have been estimated in our previous study (S.I. 1, Table S13) [44].

Solving the MOO problem

Genetic Algorithms (GAs) can be particularly useful in supporting decisions at the very early stages of complex real world problems, where limited information, multiple parameters and conflicting goals need to be overcome by exploring a wide range of possible solutions best suited for a set of circumstances or constraints [39, 58, 59]. The present study has therefore looked at the application of GAs to design an ISN such that the minimum criteria of participation are fulfilled and each participating industry has access to recovered material from the source. Here, the problem is expressed as an allocation problem where the GA explores the possible solution space with the aim of simultaneously assessing multiple objectives. The problem was solved using the MATLAB GA toolbox. The performance of the ISN considers the cumulative performance based on the GA MOO method being applied to the 7 different material streams.

A population of good solutions (GAs use the principle of natural selection) was generated while considering both objective functions (Eqs. 1 & 2) [18]. For effective design and development under rapidly changing scenarios, higher-level decision-making will be required to identify one solution for a given set of circumstances (in this case from the solution set). We propose the use of the ε-constraint method to identify this solution. Thus, the proposed hybrid method aims to leverage the strong exploratory nature of GAs in combination with the ε-constraint method to converge on one solution to efficiently allocate resources in the ISN.

The ε-constraint method is an exact solution scalarization MOO method. The problem is expressed as a single objective optimization problem by expressing other objectives as constraints. Especially useful for multi combinatorial problems, the ε-constraint method employs the use of epsilon, ε, a vector that is the upper bound of a particular constraint. Varying the ε value enables the generation of a Pareto front (PF) [5]. Given that our problem has two objectives, we can theoretically carry out the ε-constraint problem for two instances on the population of solutions generated using the GA. The first would involve expressing objective 2 (by specifying the desired net avoided impacts) as a constraint and determining the optimal value of for objective 1 (the maximum cost savings accrued). The alternative scenario is that the practitioner expresses objective 1 as a constraint (specifying the desired cost savings) and determines the optimal solution for the objective (which is now objective 2, i.e., the maximum net avoided impacts). Below, we have illustrated the implementation of ε-constraint method, i.e., prioritizing one objective function while expressing the other objective function as a constraint. While prioritizing one objective function, ε represents the upper bounds of the new objective function constraint, and is simply the corresponding solution of the auxiliary objective function(s) generated using the GA. Given below is the generic representation of the ε -constraint method for 2 objective functions.

Mathematical representation of the ε -constraint method for objective functions, *y*(1) and *y*(2)

Case 1: Maximize Cost Savings: Using standard practice, we minimize the -ve of cost savings function which is equivalent to maximizing cost savings. Hence,

$$
\begin{aligned}
&(\text{Minimize}) y(1)\\
&\text{s.t.}\\
&D_i < T_i\\
&C_{Ii} \leq .05 * T_i\\
&y(2) \leq \varepsilon_2
\end{aligned}
$$

Case 2: Maximize Net Avoided Impacts: Again, using standard practice, we solve the minimization problem for -ve of net avoided impacts. Hence,

$$
\begin{aligned}
&(\text{Minimize}) y(2)\\
&\text{s.t.}\\
&D_i < T_i\\
&C_{Ii} \leq .05 * T_i\\
&y(1) \leq \varepsilon_1
\end{aligned}
$$

Scenario analysis

This study compares the ISN resulting from the proposed hybrid MOO (Scenario D) method with alternative ISN outcomes (Scenarios A through C). These are described briefly below:

1. Scenario A: Business as Usual (BaU), i.e., EoL PVs are landfilled (Fig. 2).
2. Scenario B: Recovered material is consumed 100% (supply is equal to demand) by geographically close and distant industries (Fig. 3).

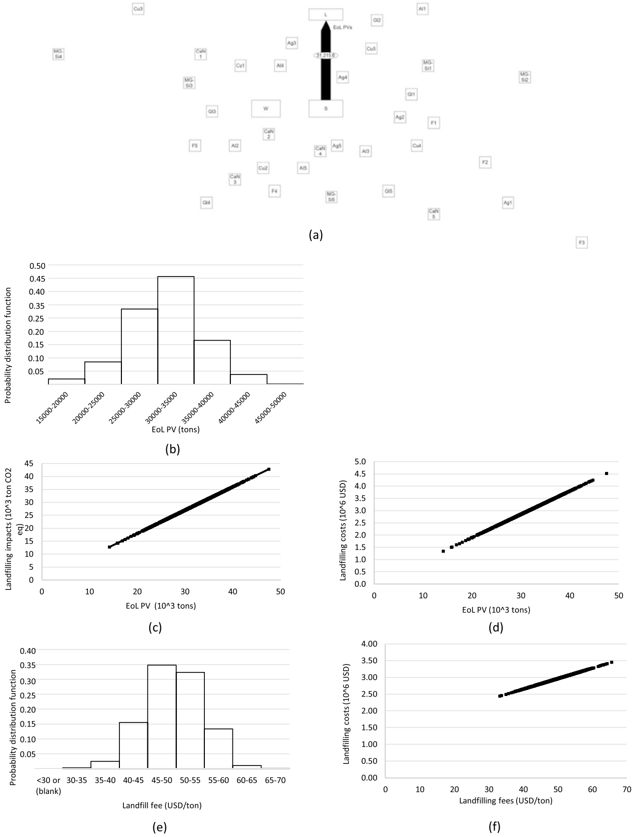


Fig. 2 (**a**) A lack of industrial synergies resulting in EoL PVs (~31,000 tons in 2030) being disposed to the landfill; (**b**) A probability distribution of possible EoL PV waste generated in 2030 (based on regular (~9071 tons) and early loss (~53,360 tons) estimates, and standard deviation of 5000 tons); (**c**) The impact of varying EoL PV quantities on the environment from landfilling (**d**) The impact of varying EoL PV quantities on costs (USD) (e) A probability distribution function of possible landfilling costs (USD/ton) (f) The impact of varying landfill 'tipping' fees on the cost of disposal (USD)

3. Scenario C: Recovered material is not consumed 100% (supply is not equal to demand) by geographically close and distant industries (Figs. 4, 5(c) and (d)) and a need for excess inventory storage arises. The economic and environmental impacts of distance between source and consumer are investigated using sensitivity analyses (Fig. 5(a) and (b)).
4. Scenario D: Recovered material (supply is not equal to demand) is allocated to partnering industries, landfilled and/or warehoused using the proposed hybrid MOO method (Fig. 6(a)).

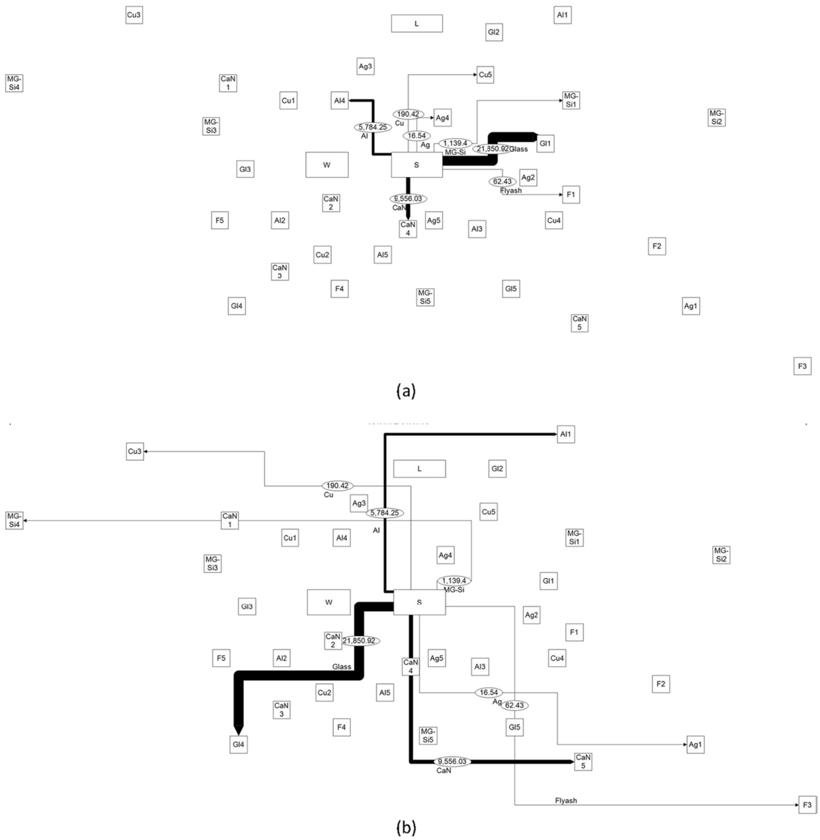


Fig. 3 (**a**) Supply equals demand (one consumer per material stream) resulting in industrial synergies between the source S, and geographically near industries (Cost savings = USD 53,384,945; Avoided impacts = 20,590.99 ton CO2 eq); (**b**) Supply equals demand (one consumer per material stream) resulting in industrial synergies between the source S, and geographically distant industries (Cost savings = USD 53,381,543; Avoided impacts = 16,314.34 ton CO_2 eq)

It should be noted that scenarios A through C represent a non-egalitarian approach to ISN design, i.e., each material stream is assigned to just one consumer per material stream. In reality, it is possible that within a region several industries have a demand for cheaper feedstock. In such a scenario, it becomes essential to develop a tool to assess the economic and environmental tradeoffs associated with fulfilling demands across multiple consumers. Scenario D (Fig. 6(a)) investigates an egalitarian ISN where cheaper feedstock/resources are shared among industries within a region by developing a hybrid MOO model. The resulting ISNs from Scenarios A through D are compared relative to cost and environmental burdens.

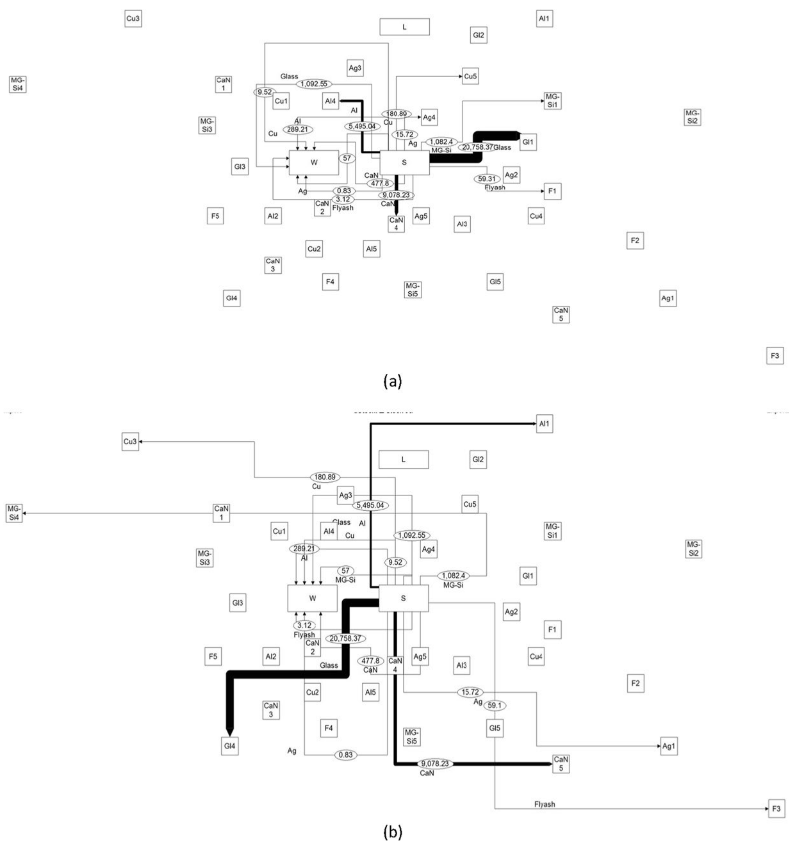


Fig. 4 (**a**) Supply surfeit resulting in warehousing needs in combination with industrial synergies (one consumer per material) between the source S, and geographically near industries (Cost savings = USD 46,742,536.52, Avoided impacts = 22,366.91 ton CO_2 eq); (**b**) Supply surfeit resulting in warehousing needs in combination with industrial synergies (one consumer per material) between the source S, and geographically distant industries (Cost savings = USD 34,394,945.04, Avoided impacts = 21,066.4 ton CO_2 eq)

Results & discussion

1The proposed hybrid method has been tested for designing an EoL PV-centric ISN. The performance of the resulting ISN in terms of balancing sustainability trade-offs and resource allocation using the hybrid MOO method (Scenario D) is evaluated and compared with alternative scenarios (Scenarios A through C). Figures 2 through 6 illustrate the hypothetical ISN under different scenarios. The node *S* in ISN are the source of recovered feedstock, (EoL PV installation/ decommissioning unit); W, the storage warehouse (offsite) for excess material; L, the landfill and the participating industries. Entities Al1 through Al5 represent aluminum consuming industries. Similarly, Gl1-Gl5, Ag1-Ag5, Cu1-Cu5, MG-Si1-MG-Si5, CaN1-CaN5, and F1–F5 represent industries that use glass, silver, copper, metallurgical grade silicon, calcium nitrate, and fly ash as feedstock respectively. The width of the flows is based on the material quantity being transported between the various participating stakeholders. It should be noted that the

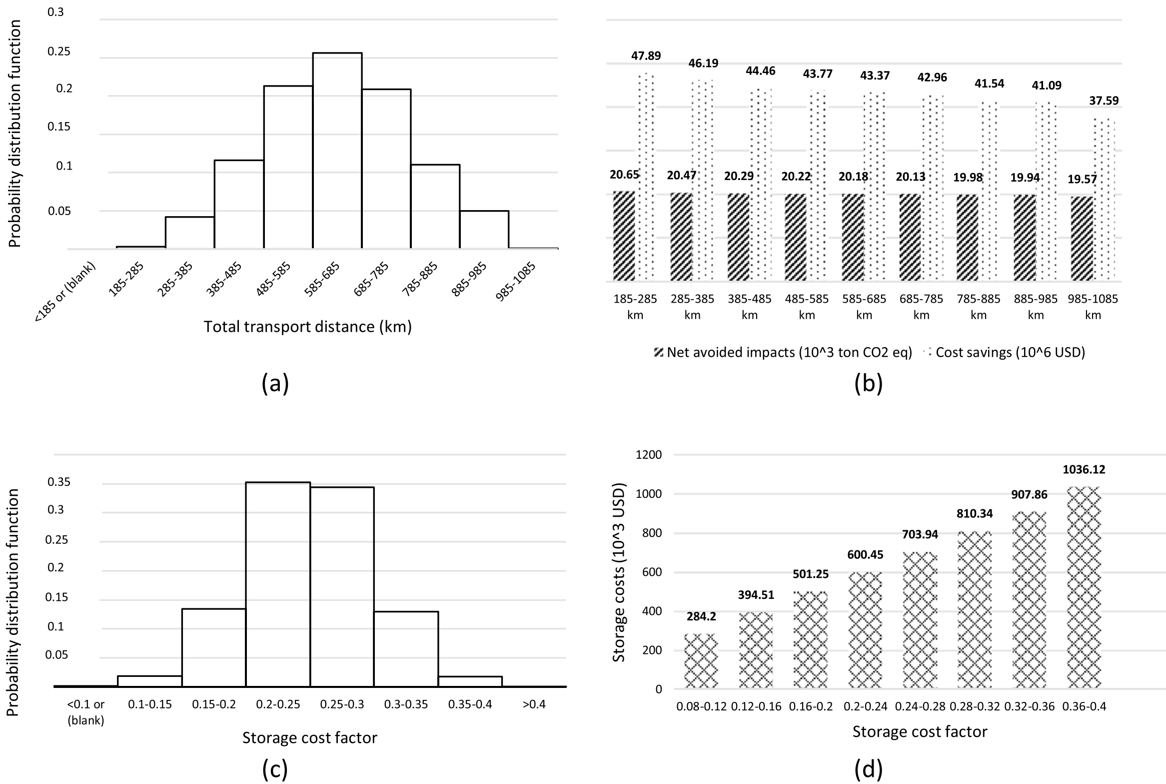
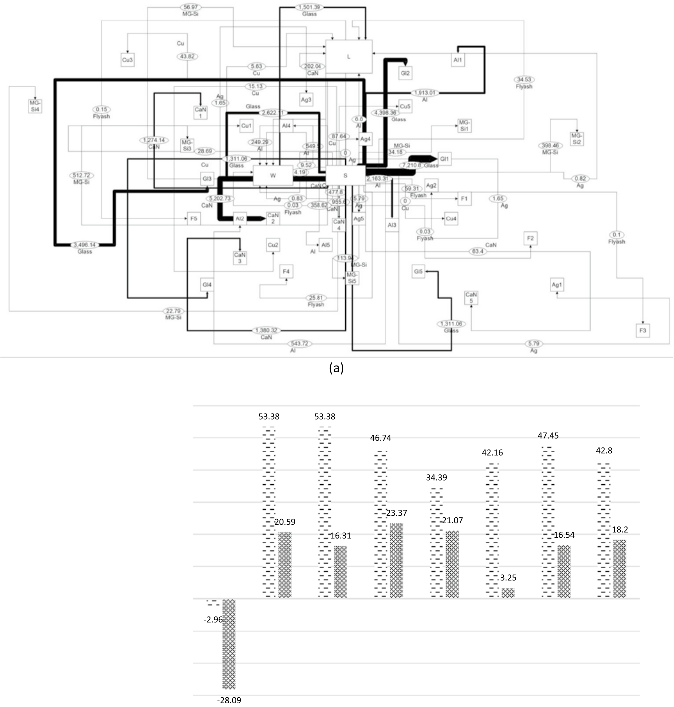


Fig. 5 (**a**) A probability distribution for the total possible distance material must be transported in the industrial network (mean = 633 km and standard deviation = 150 km); (**b**) The avoided environmental impacts and cost savings under different distance conditions; (**c**) A probability distribution for possible storage cost factors; storage cost = storage cost factor * cost of virgin material; mean storage cost factor = 0.25, standard deviation = 0.05); (**d**) Storage/warehousing costs when supply is greater than demand (Also see S.I. 3 and S.I. 4 for details related to each of the 7 material streams)



	Scenario A	Scenario B (a)	Scenario B (b)	Scenario C (a)	Scenario C (b)	Scenario D (heuristic MOO)	Scenario D (hybrid MOO-case 1)	Scenario D (hybrid MOO-case 2)
Cost savings (*10^6 USD)	-2.96	53.38	53.38	46.74	34.39	42.16	47.45	42.8
Avoided impacts (*10^3 ton CO2 eq)	-28.09	20.59	16.31	23.37	21.07	3.25	16.54	18.2

(b)

Fig. 6 (**a**) The ISN resulting from applying the hybrid MOO method (EoL PVs waste directed to landfills is down to 6%–9%); (**b**) A comparison of average cost savings (losses in case of Scenario A) and average net avoided impacts (incurred environmental impacts in case of Scenario A) resulting from discussed ISN scenarios

computations are based on the data presented in S.I. 1, and the transportation costs and impacts considerations have been integrated in the mathematical model.

Scenario A: The impact of landfilling EoL PVs

EoL related regulations for EoL PVs is presently in the nascent stages. This means that in several parts of the United States EoL PVs can be classified as non-hazardous waste resulting in them being landfilled. Scenario A assumes that EoL/broken PVs when decommissioned are transported back to the solar PV installation/decommissioning facility, S, in Fig. 2(a), where PV cells are sorted from other auxiliary material (e.g., Balance of System (BoS) material), and subsequently sent to the landfill. Under this scenario, it is likely that about 31,000 tons of EoL PVs could possibly be landfilled in Arizona by 2030. This translates to about 3 million USD in costs and 28 thousand ton CO_2 eq in global warming potential (GWP) impacts on average. Depending on whether EoL PVs are generated as a consequence of early-loss due to breakage, or regular-loss after more than two decades of operational life, the cost of landfilling EoL PVs could be between 1.35 and 4.5 million USD (Fig. 2(d)). Similarly, the range of the associated environmental impacts was found to be 15 to 43 thousand ton CO_2 eq (Fig. 2(c)) (See S.I. 2). We also considered the uncertainty associated with the landfill tipping fees. By varying this parameter (Fig. 2(e)) we have assessed its impact on disposal costs incurred. It was observed that varying the landfill tipping fees resulted in total EoL PV landfilling costs in the range of 2.46 and 3.45 million USD (Fig. 2(f)).

Scenario B: Recovered material is consumed wholly within the ISN (supply equals demand)

In contrast to Scenario A, Scenario B represents two cases where EoL PVs are recovered as 7 individual material streams and subsequently fulfill raw material demands in the form of secondary feedstock by local industries. Figure 3(a) represents the case where the recovered materials are consumed as a consequence of industrial synergies developed with firms closest to the source, S (See S.I. 1 for list of identified industries). Figure 3(b) represents the alternate extreme case of industrial synergies with firms farthest away from S (see S.I. 1). Supply equals demand and therefore it is assumed that no material is landfilled or stored. This means that the resulting differences in impacts, both economic and environmental are the result of differences in the transportation differences. While the cost savings as a result of developing industrial synergies for both cases is comparable, the net avoided impacts as a consequence of recovered material being transported under 3 (a) is about 4300 ton CO_2 eq higher than those observed for 3 (b) (See S.I. 2).

Scenario C: The impact of material storage on the ISN (supply is not equal to demand)

Under the circumstances of supply being greater than demand, it is assumed that the ISN should accommodate excess supply in storage. For the present case, it is assumed that the warehouse is located offsite and storing excess material incurs a fee called a carrying cost. We have assumed this to be 25% of the material value (See S.I. 1) [32, 52]. As in Scenario B, Scenario C also examines the cost savings and avoided environmental impacts of recovered material consumption for industries closest (Fig. 4(a)) and furthest away (Fig. 4(b)) geographically. The impact of material storage as a result of it not being 'sold' or consumed with differences in transport distances results in significant differences in cost savings (~ 12 million USD) between the two cases. On taking a closer look at the results of individual material streams, it was seen that lower sales of recovered material to the geographically close partnering firms resulted in overall positive cost savings and positive net environmental impacts. This was not the case when material was sold to firm that were geographically distant. In this case, both glass and fly ash incurred an economic loss (negative cost savings), thus driving down the overall profitability of the ISN (See S.I. 4).

Sensitivity analyses: Transport distance and storage cost

In order to understand the impact of uncertainty associated with storage costs (we have assumed storage costs are 25% of the cost of virgin resources as a base case) and the critical distances at which synergistic partners should be located (particularly for low value materials such as glass and fly ash), we have carried out sensitivity analyses on both these parameters.

A Monte Carlo (MC) simulation was carried out to vary the distances the recovered materials from EoL PVs could possibly need to be transported across. The total range of the distance all seven materials would need to be transported varied between 185 km and 1085 km (Fig. 5(a)). On average, the total cost savings decreased from about 47 million USD to 37 million USD, and the associated avoided GWP impacts were found to decrease from 20.65 thousand to 19.57 thousand ton CO_2 eq as the transportation distance increased. Specifically for glass, transportation beyond 30 km results in economic losses. The net avoided impacts of developing a regional synergy for glass were found to be negative, indicating that the best possible option for glass should be closed-loop and/or internal recycling by the PV manufacturers themselves (See S.I. 4). With regard to glass, it should be noted that it is a low-value commodity and is extremely energy-intensive to recycle. The very high quantities of glass in PVs means recovered glass quantities too are extremely high and impacts (cost and environmental) associated with transporting them will be significant given its mass and low-value. Similarly, in the case of fly ash, the critical distance beyond which a synergy was not economically profitable was 197 km. Like glass, fly ash too incurred negative net avoided impacts as a consequence of recovery and subsequent transport to a consumer, indicating internal consumption (as construction fillers) may be the most suitable option (See S.I. 4 for material-wise analysis).

Given the uncertainty associated with storage costs, a MC simulation was carried out on the storage cost parameter (Fig. 5(c)). A range was chosen to account for lack of accurate warehousing cost data (storage costs = storage cost factor * cost of material; storage cost factor ranges from 0.08–0.4). The average overall cost of storage was in the range of 700 thousand USD. As mentioned earlier, these costs take into account the uncertainty associated with non-sales and material depreciation, apart from warehousing costs.

Scenario D: The impacts of applying an MOO method to developing an ISN

Finally, we consider a more complex scenario of several stakeholders in an ISN with different material demand for each firm participating in ISN and total supply being unequal to total demand. As before, the creation of industrial synergies were for all 7 material streams that were recovered from EoL PVs. An egalitarian approach such as this, can address the potential brittleness as consequence of identifying and developing merely one synergy per material stream. This brittleness could potentially translate to losses (both economic and also goodwill among collaborators) if there is a disruption in supply, and/or lack of demand, which could in turn result in excessive inventory costs and/or material landfilling. Built-in contingencies in the form of a distributed network can help address such uncertainty. A MOO approach to balance sustainability objectives while also addressing material allocation requirements may provide insight into creating synergies that are profitable and also potentially long-lasting. A heuristic MOO method, GA, was applied to this case. The model considered the cost saving and net avoided environmental impacts while also working towards efficiently allocating material between multiple consumer, storage, and the landfill. Using GAs resulted in the generation of a population of ‘reasonable’ solutions. The average cost savings were in the range of 42 million USD, at an average environmental cost of 3.25 thousand ton CO_2 eq. It was observed that while the demands for high value material streams were being satisfied, medium (calcium nitrate solution) and low value materials (glass and fly ash) were getting landfilled. On analyzing the solution set more closely and observing each individual material stream allocation, it was found that the quantity of landfilled material ranged from 10,885 to 17,197.45 tons (34% - 54% of total material) out of about the total 31,000 tons of EoL PV that was initially in circulation, thus explaining the poor fulfillment of the environmental objective (Fig. 6(b)(See S.I. 5, Table S5.3 and Fig. S5.1).

A hybrid MOO was applied to the population of generated GA solutions using the ε constraint approach. In the first instance (Case 1), we aim to maximize the cost savings. The amount of material assigned the landfill is reduced to 2833.27 tons (~9% of EoL PVs in circulation) with cost savings now approximately ~47 million USD, but with avoided environmental impacts much higher than what was observed before with the GAs (~16 thousand ton CO_2 eq). Most notably glass, copper and metallurgical grade silicon were being allocated to industries more strategically. In the next instance (Case 2), the reverse was carried out by expressing maximization of net avoided impacts as the primary objective. Figure 6(a) depicts the ISN resulting from applying the hybrid MOO method with avoided impacts being expressed as the objective function (hybrid-MOO Case 2). Although cost savings were ~ 43 million USD and the avoided environmental impacts were at more than 18 thousand ton CO_2 eq. It should be noted, that the material landfilled was observed be less than 6% in this case (See S.I. 5, Table S5.4). The hybrid MOO method allocating material to the landfill indicates backup synergies need to be created, or alternatively ISNs must have be able to accommodate potential feedstock in larger storage facilities till such time as further demand is created.

The hybrid MOO scenario considers the transportation of material from the source to each industry. An alternative analysis on pooling materials is considered. This was found to be significantly more efficient in terms of transportation impacts in that the total transportation impacts as result of material pooling was a mere 4% of the originally considered transportation scenario (See S.I. 6).

While the overall performance in terms of maximizing the avoided environmental impacts is better for the non-egalitarian scenarios, we believe Scenario D, where multiple consumers could potentially be interested in purchasing low-cost recovered material is realistic. Specifically, the hybrid MOO method, is found to be particularly useful in its ability to allocate recovered resources effectively taking into account cost and environmental impact. Thus, apart from the model's ability to balance different objectives, in this case, it also serves to solve a combinatorial problem (material allocation between industries, warehouse, and/or landfilling).

The main advantage of using the hybrid optimization method is that it leverages the strengths of both heuristic and exact solution optimization methods, i.e. a thorough exploration of the search space followed by aggressively converging on an optimal solution based on possibly changing circumstances and constraints. In summary, this study highlights the importance of judicious of higher-level decision-making when it comes to determining which objective to consider as the primary objective and which objective(s) to express as auxiliary constraints. This could potentially be challenging when users are faced with numerous objective functions and constraints.

Summary & conclusions

This study models the development of industrial synergistic networks using the case of EoL PVs. By analyzing different scenarios, the study highlights the challenges and considerations associated with developing and evaluating ISNs. A hybrid MOO model has been proposed to create ISNs from a self-organizing, egalitarian perspective to minimize risks related with supply and demand differences, or other disruptions that could affect industrial synergies. The model also highlights the different combinatorial possibilities in an ISN to effectively balance profitability and environmental impacts based on demand and distance parameters. Importantly, it successfully balances the economic and environmental goals by diverting resources away from the landfill. Though less profitable in the short-term (owing to storage and transport costs), this is important as demand and supply are dynamic and material storage could be an important factor in mitigating supply chain risks and in maintaining industrial synergies.

Other issues the model sheds light on is the importance of considering the economic value of each recovered material stream and the role this plays in the overall performance of the model. The choice of which objective to consider and which objective(s) to express as objective function constraints calls for judicious decision-making too. The model has some obvious limitations. It does not consider the social and/or behavioral aspects of developing synergies. Further study into regulatory measures related to evolving landfilling costs, disposal penalties and policies should be accounted for. This is especially relevant to clean technologies owing to their growing demand and need for proper disposal infrastructure. Infact, more work to model alternative transportation scenarios needs to be carried out keeping in mind that this decade will present greater access to electric vehicles and considering that manufacturing could be supported in a greater degree by electricity generated less by fossil fuels and more from renewables. This could result in tangibly higher environmental benefits that in turn could further drive material recovery and the development of complex ISNs. In future it would be beneficial to also analyze remanufacturing scenarios. Unfortunately, at this time, the authors were limited in this regard owing to insufficient data on PV disassembly relative to the sub-assemblies and/or components that can potentially be recovered. Specific data needs to facilitate such an analysis would include understanding the lifetimes and extents of degradation of individual components and sub-assemblies. In addition, it would also be important to determine whether a market could be created for remanufactured EoL PV components and sub-assemblies. This study is limited only to optimizing global warming impacts (because of recovery processes and transportation) and recovery costs in the context of developing industrial synergies in a region. The proposed model can be expanded and should simultaneously account for optimizing other environmental impact categories such as water footprint, ozone depletion, eutrophication, acidification potential, etc. and not just global warming potential by constructing additional objective functions and modeling other constraints.

Finally, from a technical point of view, further complexity with regard to the constraints governing disposal and storage are required. Bi-directional material exchanges and a greater number of material sources also need to be considered. Unfortunately, the size of the model prevents us from accurately determining the impact of the choice of ε value on the model behavior (relatively small changes occur in relation with overall ISN performance since it is mainly the allocation of low value materials that need to further optimization). Scaling up the model (whether in the context of EoL PVs or other EoL consumables) to include more nodes (industries), and other objectives and constraints will help understand related uncertainties and associated sensitivities better. In this study we have analyzed individually recovered material streams from EoL PVs recovery.

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Data availability Data is available in article supporting information. This article uses data related to EoL PV waste generation, which is provided in supplementary files, distances of participating industries in the ISN, cost of material streams and impact data obtained from relevant LCI.

Declarations

Conflict of interest The authors declare no conflict of interest.

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