A Multi-Objective Model for Solar Industry Closed-Loop Supply Chain by Using Particle Swarm Optimization

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ABSTRACT

Solar energy industry is an exceptional industry which desperately relies on government support and subsidy. The demand is decreasing since the government support reduction, moreover, the dramatically increase China solar manufacturers have great impact on solar product price in recent years. Because the insufficient supply of silicon materials carries the issue of solar cell recycle, the solar manufacturer must design a sustainable closed-loop supply chain (CLSC) to recycle and reuse the retired solar cells to achieve 3E (Effective, Efficient, Environmental; 3E) objectives. This paper studies an integrated CLSC network design problem with sustainable concerns in the solar energy industry. We are interested in the logistics flows, capacity expansion and technology investments of existing and potential facilities in the multi-stage CLSC. Therefore, a deterministic multi-objective mixed integer programming model capturing the tradeoffs between the total cost and the carbon dioxide (CO_2) emission is developed to tackle the multi-stage CLSC design problem from both economic and environmental perspectives. Due to the multi-objective nature and computational complexity, a multi-objective particle swarm optimization (MOPSO) with novel flow assignment algorithms is designed to search non-dominated /Pareto CLSC design solutions. Finally, a case study of crystalline solar energy industry is illustrated to verify the proposed multi-objective CLSC design model and demonstrate the efficiency of the developed MOPSO algorithm in terms of computational time and solution quality.

1. INTRODUCTION

Consumers are becoming more aware of the environmental and social implications of their day-to-day consumer decisions and are therefore beginning to make purchasing decisions related to their environmental and ethical concerns [1]. Sustainable Enterprise is an organization that promotes sustainable living through sustainable production of goods and services, to provide solutions for fulfilling elementary needs to improve the lives of people, now and in the future with least possible environmental impact and the highest possible economic and social yield. Enterprises not only have to comply with the laws and regulations, but also need to increase the production efficient, maintain the profit, and raise the competitiveness with the low carbon emission. A sustainable supply chain with low carbon, 3E (Effective, Efficient, Environmental; 3E) and robust concepts has been a guarantee for the CSR and competitive profitable products.

The new concept of End-of-Life (EOL) product recycling, disassembling, repairing, and refurbishing is in vogue which can be defined as a closed-loop supply chain (CLSC) for sustainable enterprises. The operation concept mixing the EOL recycling provides a revolution way to supply raw materials, reduces the fabrication cost, and lower the resource consumption. In this scenario, forward and reverse logistics (FL/RL) have to be considered simultaneously in the network design of entire supply chain. Özceylan and Paksoy [2] proposed a new mixed integer mathematical model for a CLSC network that includes FL/RL with multi-periods and multi-parts. Pishvaee and Razmi [3] also interested in using the fuzzy mathematical programming based on product life cycle assessment (LCA) method to assess and quantify the environmental impacts for CLSC network configuration.

Moreover, the environmental and economic impacts also need to be adopted and optimized in supply chain design. Chaabane *et al.* [4] introduce a mixed-integer linear programming based framework for sustainable supply chain design that considers LCA principles in addition to the traditional material balance constraints at each node in the supply chain. The framework is used to evaluate the tradeoffs between economic and environmental objectives under various cost and operating strategies in the aluminum industry. Wang *et al*. [5] also studied a supply chain

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network design problem with environmental concerns. They are interested in the environmental investments decisions in the design phase and propose a multi-objective optimization model that captures the trade-off between the total cost and the environment influence. Fahimnia *et al.* [6] found that variations in cost and environmental impacts occur over ranges of carbon pricing, furthermore, built the foundation for optimization of carbon in CLSC environment. The significant incremental improvement in carbon emissions reduction happens to be in the CLSC while the carbon price range is appropriated.

This article particularly will build the CLSC model and solution suggestions based on Particle Swarm Optimization (PSO) algorithm, a heuristic global optimization method. PSO was proposed by Kennedy and Eberhart [7], they claimed each particle movement is guided by their own best known position in the search-space as well as the entire swarm's best known position. The particles are able to retain their previous positions and search the better positions, guide the swarm movements, in the end, the satisfactory solution will eventually be discovered via the optimal position process searching. Many studies have used PSO to solve the NP-hard linear programming problems.

Particle swarm contains two concepts, one is that Boyd and Richerson [8] proposed individual will refer to their own experience or experience of others in decision making according to the human decision process. The other is to propose simple rules to modularize collective natural behavior. Basically, the complicated collective behavior can be simulated by the three following aspects: follow the individual closest to objects, move towards object, and move toward group center. In PSO algorithm evolution, Naka et al. [9] introduced hybrid PSO (HPSO) which owns critical factors of W, R_1, R_2, to converge the algorithm solutions for a practical distribution state estimation. This study will replace the random variables of R_1, R_2 by using the value of C_r. Chung et al. [10] have declared that the C_r with the formula of $Cr(n+1) = k \times Cr(n) \times (1 - Cr(n))$ results in the better convergence for PSO algorithm. This study will adopt the nonlinear function to obtain the dynamic inertia weights which fit in with high dimension of PSO problems. The formula of nonlinear function is shown in Equation (1) which given a reasonable selection of w should decrease gradually while the swarm search progresses.

$$w(t) = \left(2/t\right)^{0.3} \tag{1}$$

w(t) represents the inertia weight of t generations; t represents the t generation.

2. Multi-Objective Closed-Loop Supply Chain Design

This paper will discuss the relationship of FLs and RLs, the plant locations of RLs, the capacity of CLSC, and carbon emission issues. The proposed new CLSC is expected to reach the environmental and economic benefit by considering various levels of carbon emission manufacturing process and invested cost. A multi-objective mixed integer programming model is formulated to solve the multi-stage CLSC problem with economic and environmental performances in this section. The assumptions used in this model are: (1) The number of customers and suppliers and their demand are known, (2) Second market is unique, (3) The demand of each customer must be satisfied, (4) The flow is only allowed to be transferred between two consecutive stages, (5) The number of facilities that can be opened and their capacities are both limited, (6) The recovery and disposal percentages are given. The indices, input parameters, and decision variables of the multi-objective CLSC design model are defined as follows:

Indices

s	Index for material suppliers ($s = 1,\ldots,S$)
i	Index for production stages of forward supply chain ($i = 1,\ldots,I$)
$\Phi(i)$	Set of existing production units in each stage *i* of forward supply chain ($\Phi(i) = \{1,\ldots,Num(i)\}$)
(i,k)	Existing production unit *k* in stage *i* of forward supply chain, where $k \in \Phi(i)$
c	Index for end customers ($c = 1,\ldots,C$)
j	Index for recycling stages of reverse supply chain ($j = 1,\ldots,J$)
$\Psi(j)$	Set of potential recycling units in each stage *j* of reverse supply chain ($\Psi(j) = \{1,\ldots,Num(j)\}$)
(j,p)	Potential recycling unit *p* in stage *j* of reverse supply chain, where $p \in \Phi(j)$
l	Index for capacity expansion levels ($l = 1,\ldots,L$)
t	Index for technology types ($t = 1,\ldots,T$)

Parameters

- Cost related parameters

pc_s^{rm}, pc_j^{sm} Purchasing cost from material supplier and secondary market in RL

$dc_{(j,p)}$	Disposal cost in potential recycling unit of stage
sc_{sk} , $sc_{(i,k)(i',k')}$, sc_{kc} ; sc_{cp} , $sc_{(j,p)(j',p')}$, $sc_{(j,p)(i,k)}$	Transportation cost in FL and RL
$mc_{(i,k)t}, mc_{(i,p)t}$	Production cost using technology level t at potential production unit k in stage i and potential recycling unit p in stage j
$bc_{(j,k)}, bc_{(j,p)}$	Fixed installation cost of potential recycling unit k and p in stage j
$cc_{(i,k)tl}$, $cc_{(j,p)tl}$	Capacity expansion cost of each capacity level using each technology type at existing production unit and potential recycling unit

- Capacity related parameters

$cl_{(i,k)tl}$, $cl_{(j,p)tl}$	Expanded capacity amount of each capacity level using each technology type at existing production unit and potential recycling unit

- Supply & Demand related parameters

s_s^{rm} , s_j^{sm}	Supply quantity of material supplier and secondary market
d_c , r_c	Demand and Recycling quantity of customers c

- Environment related parameters

$pce_{(i,k)t}$, $pce_{(j,p)t}$	Carbon emissions quantity of each technology type at existing production unit and potential recycling unit
$puce_{(i,k)t}$, $puce_{(i,p)t}$	Carbon emissions quantity of technology level t at potential production unit k in stage i and recycling unit p in stage j
tce_{sk} , $tce_{(i,k)(i',k')}$, tce_{kc} ; tce_{cp} , $tce_{(j,p)(j',p')}$, $tce_{(j,p)(i,k)}$	Carbon emissions quantity for transportation in FL and RL

- Logistic related parameters

t_{sk} , $t_{(i,k)(i',k')}$, t_{kc} ; t_{cp} , $t_{(j,p)(j',p')}$, $t_{(j,p)(i,k)}$	Minimum transportation quantity in FL and RL

- Ratio related parameters

$\lambda_{(j,p)}^{dis}$	Disposal percentage of potential recycling unit p in stage j
γ_{ji}^{ret}	Recovery percentage from stage j of reverse supply chain to stage i of forward supply chain

Decision Variables

- *Continuous Variables*

TQ_{sk} , $TQ_{(i,k)(i',k')}$, TQ_{kc} ; TQ_{cp} , $TQ_{(j,p)(j',p')}$, $TQ_{(j,p)(i,k)}$	Transportation quantity in FL and RL
$p_{(j,p)}$	Purchasing quantity of potential recycling unit p in stage j from secondary market
$D_{(j,p)}$	Disposal quantity of potential recycling unit p in stage j

- Binary Variables

$X_{(i,k)} = 1$, if potential recycling unit k in stage i is open; $X_{(i,k)} = 0$, otherwise.

$X_{(j,p)} = 1$, if potential recycling unit p in stage j is open; $X_{(j,p)} = 0$, otherwise.

$AC_{(i,k)tl} = 1$, if existing production unit k in stage i expands capacity level l using technology t; $AC_{(i,k)tl} = 0$, otherwise.

$AC_{(j,p)tl} = 1$, if potential recycling unit p in stage j expands capacity level l using technology t; $AC_{(j,p)tl} = 0$, otherwise.

$TA_{sk} = 1$, if supplier s ships to existing production unit k in first stage of forward supply chain; $TA_{sk} = 0$, otherwise.

$TA_{(i,k)(i',k')} = 1$, if existing production unit k in stage i ships to existing production unit k' in stage i'; $A_{(i,k)(i',k')}=0$, otherwise.

$TA_{kc} = 1$, if existing production unit k in last stage of forward supply chain ships to customer c; $TA_{kc} = 0$, otherwise.

$TA_{cp} = 1$, if customer c ships to potential recycling unit p in first stage of reverse supply chain; $TA_{cp} = 0$, otherwise.

$TA_{(j,p)(j',p')} = 1$, if potential recycling unit p in stage j ships to potential recycling unit p' in stage j'; $TA_{(j,p)(j',p')} = 0$, otherwise.

$TA_{(j,p)(i,k)} = 1$, if potential recycling unit p in stage j ships to existing production unit k in stage i; $TA_{(j,p)(i,k)} = 0$, otherwise.

2.1. MULTI-OBJECTIVE CLOSED-LOOP SUPPLY CHAIN DESIGN PROBLEM (MOCLSCD):

Objective Function

Minimize $F1 = PC + BC + MC + CEC + TC + DC$

Minimize $F2 = PCOE + BCOE + TCOE$

The purpose of the CLSC design model aims to identify the trade-off solutions between the economic and environmental performances under several logistic constraints. The economic objective, F1, is measured by the total CLSC cost. The environmental objective, F2, is measured by the total carbon (CO_2) emission in all the CLSC.

Economic objective (F1):

- Total material purchasing cost (PC)

$$\sum_{s\in S}\sum_{k\in\phi(1)} pc_s^{rm}\times TQ_{sk} \quad (1) \qquad \sum_{j\in J}\sum_{p\in\Psi(j)} pc_j^{sm}\times P_{(j,p)} \quad (2)$$

- Total installation cost (BC)

$$\sum_{i\in I}\sum_{k\in\Phi(I)} bc_{(i,k)}\times X_{(i,k)} + \sum_{j\in J}\sum_{p\in\Psi(J)} bc_{(j,p)}\times X_{(j,p)} \quad (3)$$

- Total production cost (MC)

$$\sum_{s\in S}\sum_{k\in\Phi(1)}\sum_{t\in T} mc_{(1,k)t}\times TQ_{sk} \quad (4) \qquad \sum_{i=2}^{I}\sum_{k\in\Phi(i-1)}\sum_{k'\in\Phi(i)}\sum_{t\in T} mc_{(i-1,k)(i,k')t}\times TQ_{(i-1,k)(} \quad (5)$$

$$\sum_{c\in C}\sum_{p\in\Psi(1)}\sum_{t\in T} mc_{(1,p)t}\times TQ_{cp} \quad (6) \qquad \sum_{j=2}^{J}\sum_{p\in\Psi(j-1)}\sum_{p'\in\Psi(j)}\sum_{t\in T} mc_{(j-1,p)(j,p')t}\times TQ_{(j-1,p)(j} \quad (7)$$

$$\sum_{j\in J}\sum_{p\in\Psi(j)}\sum_{i\in I}\sum_{k\in\Phi(i)}\sum_{t\in T} mc_{(j,p)(i,k)t}\times TQ_{(j,p)(i,k)} \quad (8)$$

- Total capacity expansion cost (CEC)

$$\sum_{i\in I}\sum_{k\in\Phi(j)}\sum_{t\in T}\sum_{l\in L} cc_{(i,k)tl}\times cl_{(i,k)tl}\times AC_{(i,k)tl} \quad (9) \qquad \sum_{j\in J}\sum_{p\in\Psi(j)}\sum_{t\in T}\sum_{l\in L} cc_{(j,p)tl}\times cl_{(j,p)tl}\times AC_{(j,p)tl} \quad (10)$$

- Total transportation cost (TC)

$$\sum_{s\in S}\sum_{k\in\Phi(1)} sc_{sk}\times TQ_{sk} \quad (11) \qquad \sum_{i=2}^{I}\sum_{k\in\Phi(i-1)}\sum_{k'\in\Phi(i)} sc_{(i-1,k)(i,k')}\times TQ_{(i-1,k)(i,k')} \quad (12)$$

$$\sum_{k\in\Phi(i-1)} sc_{sk}\times TQ_{kc} \quad (13) \qquad \sum_{c\in C}\sum_{p\in\Psi(1)} sc_{cp}\times TQ_{cp} \quad (14)$$

$$\sum_{j=2}^{J}\sum_{p\in\Psi(j-1)}\sum_{p'\Psi(j-1,p)(j,p')} sc_{(j-1,p)(j,p')}\times TQ_{(j-1,p)(j,p')} \quad (15) \qquad \sum_{j\in J}\sum_{p\in\Psi(j)}\sum_{i\in I}\sum_{k\in\Phi(i)} sc_{(j,p)(i,k)}\times TQ_{(j,p)(i,k)} \quad (16)$$

- Total disposal cost (DC)

$$\sum_{j\in J}\sum_{p\in\Psi(j)} dc_{(j,k)}\times D_{(j,k)} \quad (17)$$

Environmental objective (F2):

- Total production carbon emission (PCOE)

$$\sum_{s\in S}\sum_{k\in\Phi(1)}\sum_{t\in T} puce_{(1,k)t}\times TQ_{sk} \quad (18) \qquad \sum_{i=2}^{I}\sum_{k\in\Phi(i-1)}\sum_{k'\in\Phi(i)}\sum_{t\in T} puce_{(i-1,k)(i,k')t}\times TQ_{(i-1,k)(i,k')} \quad (19)$$

$$\sum_{c\in C}\sum_{p\in\Psi(1)}\sum_{t\in T} puce_{(1,p)t}\times TQ_{cp} \quad (20) \qquad \sum_{j=2}^{J}\sum_{p\in\Psi(j-1)}\sum_{p'\in\Psi(j)}\sum_{t\in T} puce_{(j-1,p)(j,p')t}\times TQ_{(j-1,p)(j,p')} \quad (21)$$

$$\sum_{j\in J}\sum_{p\in\Psi(j)}\sum_{i\in I}\sum_{k\in\Phi(i)}\sum_{t\in T} puce_{(j,p)(i,k)t}\times TQ_{(j,p)(i,k)} \quad (22)$$

- Total installation carbon emission (BCOE)

$$\sum_{i\in I}\sum_{k\in\Phi(I)} pce_{(i,k)}\times X_{(i,k)} + \sum_{j\in J}\sum_{p\in\Psi(J)} pce_{(j,p)}\times X_{(j,p)} \quad (23)$$

- Total transportation carbon emission (TCOE)

$$\sum_{s\in S}\sum_{k\in\Phi(1)} tce_{sk}\times TQ_{sk} \quad (24) \qquad \sum_{i=2}^{I}\sum_{k\in\Phi(i-1)}\sum_{k'\in\Phi(i)} tce_{(i-1,k)(i,k')}\times TQ_{(i-1,k)(i,k')} \quad (25)$$

$$\sum_{k\in\Phi(I)}\sum_{c\in C} tce_{kc}\times TQ_{kc} \quad (26) \qquad \sum_{c\in C}\sum_{p\in\Psi(1)} tce_{cp}\times TQ_{cp} \quad (27)$$

$$\sum_{j=2}^{J}\sum_{p\in\Psi(j-1)}\sum_{p'\in\Psi(j)} tce_{(j-1,p)(j,p')}\times TQ_{(j-1,p)(j,p')} \quad (28) \qquad \sum_{j\in J}\sum_{p\in\Psi(j)}\sum_{i\in I}\sum_{k\in\Phi(i)} tce_{(j,p)(i,k)}\times TQ_{(j,p)(i,k)} \quad (29)$$

Constraints

- *Material supply constraints*

$$\sum_{k\in\Phi(1)} TQ_{sk}\le s_s^{rm},\forall s\in S \quad (30)$$

$$P_{(j,p)}\le s_j^{sm},\forall j\in J,\forall p\in\Psi(j) \quad (31)$$

- *Flow conservation constraints*

$$\sum_{s\in S} TQ_{sk} + \sum_{j\in J}\sum_{p\in\Psi(j)} TQ_{(j,p)(i,k)} = \sum_{k'\in\Phi(i+1)} TQ_{(i,k)(i+1,k')} \qquad \forall i=\{1\},\forall k\in\Phi(1) \quad (32)$$

$$\sum_{k'\in\Phi(i-1)} TQ_{(i-1,k')(i,k)} + \sum_{j\in J}\sum_{p\in\Psi(j)} TQ_{(j,p)(i,k)} = \sum_{k'\in\Phi(i+1)} TQ_{(i,k)(i+1,k')} \quad \forall i=\{2,\ldots,I-1\}, \forall k\in\Phi(i) \tag{33}$$

$$\sum_{k'\in\Phi(I)} TQ_{(i-1,k')(i,k)} + \sum_{j\in J}\sum_{p\in\Psi(j)} TQ_{(j,p)(i,k)} = \sum_{c\in C} TQ_{kc} \quad \forall i=I, \forall k\in\Phi(I) \tag{34}$$

$$\sum_{k\in\Phi(I)} TQ_{kc} + N_c = d_c \quad \forall c\in C \tag{35}$$

$$\sum_{p\in\Psi(j)} TQ_{cp} = r_c \quad \forall c\in C \tag{36}$$

$$\sum_{c\in C} TQ_{cp} + P_{(j,p)} = \sum_{p'\in\Psi(j+1)} TQ_{(j,p)(j+1,p')} + D_{(j,p)} + \sum_{i\in I}\sum_{k\in\Phi(i)} TQ_{(j,p)(i,k)} \quad \forall j=\{1\}, \forall p\in\Psi(1) \tag{37}$$

$$\sum_{p'\in\Psi(j-1)} TQ_{(j-1,p')(j,p)} + P_{(j,p)} = \sum_{p'\in\Psi(j+1)} TQ_{(j,p)(j+1,p')} + D_{(j,p)} + \sum_{i\in I}\sum_{k\in\Phi(i)} TQ_{(j,p)(i,k)} \quad \forall j=\{2,\ldots,J-1\}, \forall p\in\Psi(j) \tag{38}$$

$$\sum_{p'\in\Psi(j-1)} TQ_{(j-1,p')(j,p)} + P_{(j,p)} = D_{(j,p)} + \sum_{i\in I}\sum_{k\in\Phi(i)} TQ_{(j,p)(i,k)} \quad \forall j=J, \forall p\in\Psi(J) \tag{39}$$

$$D_{(j,p)} = \lambda^{dis}_{(j,p)} \times \left(\sum_{c\in C} TQ_{cp} + P_{(j,p)}\right) \quad \forall j=\{1\}, \forall p\in\Psi(1) \tag{40}$$

$$D_{(j,p)} = \lambda^{dis}_{(j,p)} \times \left(\sum_{p'\in\Psi(j-1)} TQ_{(j-1,p')(j,p)} + P_{(j,p)}\right) \quad \forall j=\{2,\ldots,J\}, \forall p\in\Psi(j) \tag{41}$$

$$\sum_{k\in\Phi(i)} TQ_{(j,p)(i,k)} \le \gamma^{ret}_{ji} \times \left(\sum_{c\in C} TQ_{cp} + P_{(j,p)} - D_{(j,p)}\right) \quad \forall i\in I,\ \forall j=\{1\},\ \forall p\in\Psi(1) \tag{42}$$

$$\sum_{k\in\Phi(i)} TQ_{(j,p)(i,k)} \le \gamma^{ret}_{ji} \times \left(\sum_{p'\in\Psi(j-1)} TQ_{(j-1,p')(j,p)} + P_{(j,p)} - D_{(j,p)}\right) \quad \forall i\in I, \forall j=\{2,\ldots,J\}, \forall p\in\Psi(j) \tag{43}$$

- *Capacity expansion and limitation constraints*

$$\sum_{s\in S} TQ_{sk} + \sum_{j\in J}\sum_{p\in\Psi(j)} TQ_{(j,p)(i,k)} \le ca_{(i,k)} + \sum_{t\in T}\sum_{l\in L}\left(cl_{(i,k)tl} \times AC_{(i,k)tl}\right) \quad \forall i=\{1\} \quad, \forall k\in\Phi(1) \tag{44}$$

$$\sum_{k'\in\Phi(i-1)} TQ_{(i-1,k')(i,k)} + \sum_{j\in J}\sum_{p\in\Psi(j)} TQ_{(j,p)(i,k)} \le ca_{(i,k)} + \sum_{t\in T}\sum_{l\in L}\left(cl_{(i,k)tl} \times AC_{(i,k)tl}\right) \quad \forall i=\{2,\ldots,I\} \quad, \forall k\in\Phi(i) \tag{45}$$

$$\sum_{t\in T}\sum_{l\in L} AC_{(i,k)tl} \le 1 \quad \forall i\in I \quad, \forall k\in\Phi(i) \tag{46}$$

$$\sum_{c\in C} TQ_{cp} + P_{(j,p)} \le \sum\sum_{t\in T}\sum_{l\in L}\left(cl_{(j,p)tl} \times AC_{(j,p)tl}\right) \quad \forall j=\{1\}, \forall p\in\Psi(1) \tag{47}$$

$$\sum_{p'\in\Psi(j-1)} TQ_{(j-1,p')(j,p)} + P_{(j,p)} \le \sum_{t\in T}\sum_{l\in L}\left(cl_{(j,p)tl} \times AC_{(j,p)tl}\right) \quad \forall j=\{2,\ldots,J\}, \quad \forall p\in\Psi(j) \tag{48}$$

$$\sum_{t\in T}\sum_{l\in L} AC_{(j,p)tl} = X_{(j,p)} \quad ,\forall j\in J, \forall p\in\Psi(j) \tag{49}$$

- *Transportation constraints*

$$t_{sk} \times TA_{sk} \le TQ_{sk} \le TA_{sk} \times M \quad \forall s\in S \quad, \forall k\in\Phi(1) \tag{50}$$

$$t_{(i-1,k)(i,k')} \times TA_{(i-1,k)(i,k')} \le TQ_{(i-1,k)(i,k')} \le TA_{(i-1,k)(i,k')} \times M \quad \forall i=\{2,\ldots,I\} \quad, \forall k\in\Phi(i-1) \quad, \forall k'\in\Phi(i) \tag{51}$$

$$t_{kc} \times TA_{kc} \le TQ_{kc} \le TA_{kc} \times M \quad, \forall k\in\Phi(I) \quad, \forall c\in C \tag{52}$$

$$t_{cp} \times TA_{cp} \le TQ_{cp} \le TA_{cp} \times M \quad, \forall c\in C \quad, \forall p\in\Psi(1) \tag{53}$$

$$t_{(j-1,p)(j,p')} \times TA_{(j-1,p)(j,p')} \le TQ_{(j-1,p)(j,p')} \le TA_{(j-1,p)(j,p')} \times M \quad \forall j=\{2,\ldots,J\} \quad, \forall p\in\Psi(j-1) \quad, \forall p'\in\Psi(j) \tag{54}$$

$$t_{(j,p)(i,k)} \times TA_{(j,p)(i,k)} \le TQ_{(j,p)(i,k)} \le TA_{(j,p)(i,k)} \times M \quad \forall j\in J \quad, \forall p\in\Psi(j) \quad, \forall i\in I \quad, \forall k\in\Phi(i) \tag{55}$$

- *Domain constraints*

$$\begin{gathered} TQ_{s(i,k)}, TQ_{(i,k)(i',k')}, TQ_{(i,k)c}, TQ_{c(j,p)}, TQ_{(j,p)(j',p')}, TQ_{(j,p)(i,k)}, P_{(j,p)}, D_{(j,p)}, N_c \ge 0 \\ \forall s\in S, \forall i\in I, \forall k\in\Phi(i), \forall c\in C, \forall j\in J, \forall P\in\Psi(j) \end{gathered} \tag{56}$$

$$\begin{gathered} X_{(j,p)}, AC_{(i,k)tl}, AC_{(j,p)tl}, TA_{s(i,k)}, TA_{(i,k)(i',k')}, TA_{(i,k)c}, TA_{c(j,p)}, TA_{(j,p)(j'p')}, TA_{(j,p)(i,k)} \in \{0,1\} \\ \forall s\in S, \forall i\in I, \forall k\in\Phi(i), \forall c\in C, \forall j\in J, \forall P\in\Psi(j) \end{gathered} \tag{57}$$

3. PARTICLE SWARM OPTIMIZATION

In this section, a novel multi-objective PSO with ideal-point non-dominated sorting is designed to find the optimal solution of the proposed MOCLSCD model. Figure 1 demonstrates the PSO algorithm and repair process for this MOCLSCD model. The process is following (1) particle searching, coding and initializing; (3) repair mechanism using crowding distance and ideal point; (4) Fitness computation, evaluation and optimization.

(1) Particle searching, coding and initializing: randomly generating particle initial position by continuous variables and transfer continuous variable to binary variables and discrete variables.

(2) Repair mechanism: using crowding distance or ideal point to avoid the unreasonable shortage-(i) total capacity and demand balance and balance in each stage; (ii) expended factory computation; (iii) capacity expansion.
(3) Flow assignment: satisfying total demand with lowest carbon emission and cost by flow assignment
(4) Fitness computation, evaluation and optimization: (i) calculating the fitness of every particle by MOCLSC model and obtain the p_{best}; (ii) updating the gbest, C_r, velocity, position; (iii) optimization achievement.

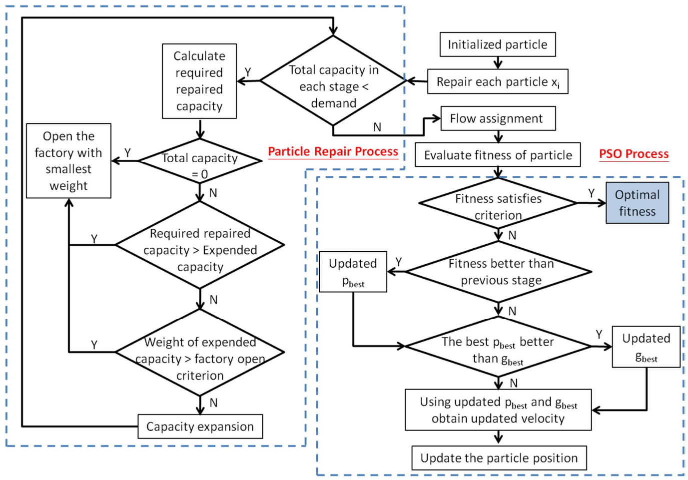

Figure 1. PSO algorithm and repair process of MOCLSCD model.

4. RESULT AND ANALYSIS

4.1. DESIGN OF EXPERIMENT (DOE) AND ANALYSIS

This study used DOE to analyze the variable range and came out the best composition of variables. Since this model is dealing with multi-objectives, we applied the ideal-point non-dominated sorting for non-dominated set to calculate F' and the distance of $d(F)$ between $\left(F_1^{'}, F_2^{'}\right)$ and zero, where $(F_1, F_2)_{x_i}$ is an element in non-dominated set; $F_1^{\max}$ and $F_2^{\max}$ the highest values of the first and second objectives among experiments; $F_1^{\min}$are lowest values of the first and second objectives among experiments. In the end, the distance will be sorted which leads to the proposed PSO.

$$F' = (F_1^{'}, F_2^{'}) = \left(\frac{F_1 - F_1^{\min} + \rho}{F_1^{\max} - F_1^{\min} + \rho}, \frac{F_2 - F_2^{\min} + \rho}{F_2^{\max} - F_2^{\min} + \rho} \right) \tag{58}$$

$$d(F) = d(F'_1, F'_2) = \sqrt{(F'_1 - F_0)^2 + (F'_2 - F_0\,)^2} \tag{59}$$

DOE is using to conclude the the best parameter set for PSO. Based on ANOVA, we obtained the best parameter set of C_1=6/C_2=6; w =0.75; C_r=varying parameters; MO method=ST; particle number=100. Using the suggested parameters to apply into PSO and compare the result to the optimal result of CPLEX based on the same parameter set. The algorithm logistic of CPLEX adopted the Branch-and-Bound (B & B) method. Three indicators are using in this study and validate the accuracy of PSO algorithm: (1) C-metric (CM) [11]; (2) maximum spread metric (*S*-metric;S(A)) [12]; (3) Maximum distance (D_{max}) [13]. Table 1 shows the performance evaluation results regarding to three indicators. Since the algorithm is unable to exceed the CPLEX optimal solution, the PSO result is better when CPLEX converge value is close to 1. The converge ability of CPLEX and PSO for 2 stages and 2 units are 0.6 and 0 in CM indicator, furthermore, the converge percentage of CPLEX and PSO are 1 and 0.3737 in S(A) indicator. The higher S(A) value of PSO indicates the PSO solutions close to the optimal solutions.

In order to validate this model can be converged in complicated problem; this study provides the convergence trend of Pareto-optimal of 7 stages and 7 units in Figure 2. We observed that the Pareto-optimal converged rapidly in the initial 4 generations. It also clearly shows the generations increased while the solution close to the lower cost and CO_2 emission. The Pareto-optimal and solution set optimal were achieved after 278 and 119 generations. These results showed that CLSC model can be optimal using PSO even though the problem is large and complicated.

Table 1. The performance evaluation of CPLEX and MOPSO.

Scenarios	Methods	CM	S(A)	Dmax
2 Stages/2 Units	CPLEX	0.6	1	0
	MOPSO	0.0	0.3737	0.1
2 Stages/3 Units	CPLEX	0.78	1	0
	MOPSO	0	0.43	0.057
3 Stages/3 Units	CPLEX	-	-	-
	MOPSO	-		

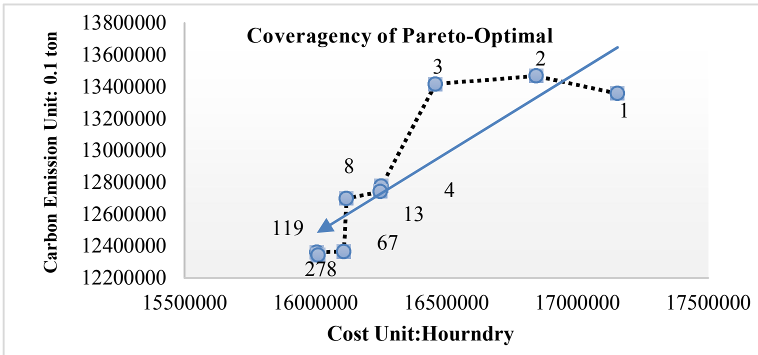

Figure 2. Pareto track of 7 stages and 7 units.

4.2. Case Study

Since the solar cell can be recycled, refurbished, and reuse, it gave the potential to create the RL in supply chain design, moreover, achieve the economic and environmental benefits for solar enterprises. The solar modules in the EOL solar products can be extracted by component separation factories and the rest can be re-processed and extract solar cells by chemical factories in RL. Solar cells will deliver to FL to refurbish or to RL for quality examination. Some solar cells after quality examination can extract the silicon materials and be reduced to silicon raw materials by silicon powder production fatories, some solar cells are good quality that will deliver to FL for reproduction, and few which didn't pass the quality examination goes to disposal factories.

Table 2. The optimal solutions of case study in different scenarios.

	Total Cost	Carbon Emission	Cost Differential (%)	CO2 Emission Differential (%)
Economic Optimal	$788,341,600	635,378 ton	-	-
Pareto Optimal	$792,846,000	629,804 ton	0.52%	-0.63%
Environmental Optimal	$805,367,600	620,492 ton	2.16%	-2.34%

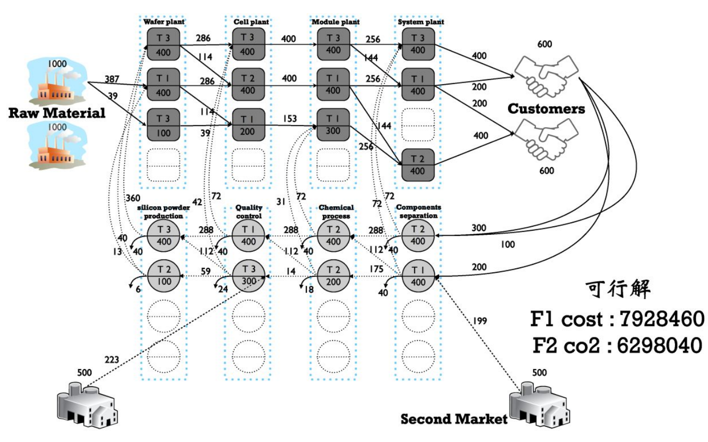

Figure 3. Pareto-optimal solution of 4 stages and 4 units.

This study applied the previous model to solve the solar industry complication CLSC problem in high dimension and more restrictions. We believe that the optimal results will assist solar enterprises to have better strategy establishment for CLSD decisions. This experiment set up 500 iterations to obtain the optimal solution. Table 3 demonstrates the single optimization results and Pareto optimization results which the decreasing carbon emission will cause the higher cost can be observed. The Pareto results will need more 0.52% cost, in addition, the environmental model will need more 2.16% cost to obtain the economic optimal. Figure 3 shows the Pareto-optimal solution of 4 stages and 4 units with compromise of economic and environmental concerns. We observed that the solution contained the all technologies which are 7 units for technology level 1, 6 units for technology level 2, 7 units for technology level 3.

5. CONCLUSION

This paper studies an integrated CLSC network design problem with cost and environmental concerns in the solar energy industry. We adjusted the factory capacity based on selecting various manufacturing technology levels, furthermore, diagnosed the economic and environmental impact based on various scenarios of FL/RL capacity and demand. While the scale of CLSC enlarging, more operated factories in FL/RL and carbon pollution will occur, in addition, the Pareto optimal solution which provided by this investigation will give the suggestions of capacity expansion, technology selection, supply chain design, factory location options, and capacity allocation based on different local regulation for enterprises. This investigation also compared the PSO solution to CPLEX and studied the efficiency and performance. For NP-hard and complicated problem, CPLEX, corresponding to PSO with high efficient and feasible optimal solutions, is limited and gives infeasible results. In the end of this report also gave a real case study in solar industry to validate the MOCLSC model by using PSO algorithm in terms of computational time and solution quality. Through the MOCLSC model, the solar enterprises are able to select the appropriated technologies to fulfill the economic and environmental concerns based on the enterprises' sustainable visions.

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