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An Effective Particle Swarm Optimization for Lot-Sizing Problem with Particulate Matter Emission Constraint

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ABSTRACT

The green supply chain is the reduction of the atmospheric release emissions including gases, vapour, smoke, solid or liquid particles. This atmospheric reduction will concern each stage of the chain: supply, production, distribution, warehousing, transport and delivery. The design of this loop is based on industrial ecological perspectives, particularly in the production, and the transport stage. In this work, we present a lot-sizing problem with capacitated one warehouse multi retailers (OWMR) under the minimization of particles matter (PM) emission from production and delivery, knowing that the problem is an NP-hard. We have developed a logistics structure containing a production unit connected to a distribution network characterized by (size, number and location) retailers specializing in a single type of product. Then, we will introduce our mathematical problem modelling using mixed-integer programming and develop an approach based on the metaheuristic called binary particle swarm optimization (BPSO) in this approach; we will study new strategies and techniques concerning the particle swarm parameters. The improved BPSO will be tested on a series of benchmark data sets and compared with CPLEX. According to the experimental results, this approach is effective in minimizing the total cost of the supply chain and promoting green technology by reducing the number of the particles emitted into the air. It also provides a decision support system to answer key questions about when and how much produce and distribute in a sustainable environment.

1. INTRODUCTION

Supply chain management (SCM) can be defined as the interconnection of three basic functions: planning, design and control (activities and flows). It starts through the supply that ends with customer satisfaction [1, 2].

Effective management of the logistics chain in a competitive environment requires effective governance in production planning. The problem of a single product, multiple periods, and inventory size are among the basic problems that affect trading and have been addressed by a group of researchers [3, 4].

Green Lot-Sizing Problem (GLSP) is considered as a tradeoff between setup and inventory holding costs to determine the minimum cost of a production plan for one or several machines, in order to meet the demand for each item with respecting the environmental constraints.

The atmospheric release inside the supply chain management is carbon emission constraint and particles matter emission constraint.

Concerning the first environmental constraint (carbon emission constraint), in Table 1, we've compared the different studies about lot-sizing problem with different carbon emission constraints thanks to the literature review. The main research gaps here are: (1) research authors, (2) model studies, (3) carbon emission policy and (4) resolution method.

Their study was to shed light on the integration of two important dimensions [5]: production planning and the principle of sustainability. The study aimed to maximize the expected gross profit of the two-stage newsstand model with environmental constraints: using the cost of licenses, emission limit values, and fines imposed in case of exceeding their permissible limits: Many authors have also focused on this topic. El Saadany et al. [6] focused on two basic approaches, one of which displays the relationship between price and demand with constant quality, and the others present the supply chain precisely affects the criteria of quality, demand, price, in addition the relationships between these criteria under the environmental constraint. In fact, the authors developed a multi-criteria decision support system based on the Pareto method under environmental (carbon emission with MRL) constraints [7] has been used by Bouchery et al. [8] in order to perform operational optimization. Benjaafar et al. [9] mentioned four different types of carbon emission constraints, which are: strict carbon caps, carbon tax, carbon emission trading and carbon. Absi et al. [10] have proposed a new classification of carbon emission constraint, unlike Benjaafar. The four types of carbon emissions are: periodic carbon emission, cumulative carbon emission, global carbon emission and rolling carbon emission [10], other Emission of pollutants such as waste and dust. Although carbon emission limits have been addressed in the majority of articles, the penalty resulting from exceeding these emission limit values has only been addressed by three authors [11, 12]. Four criteria were addressed in this study by focusing on the economic model of quantity scaling with multiple replenishment modes. Suppliers of means of transportation from an economic and environmental perspective (cost and emission level) In a study [13], the authors focused on the consumption of environmental products and how they affect carbon emissions in a complex supply chain [14]. This paper addressed a novel multi-product, multi-period replenishment problem, and proposed the nonlinear model solved by GA and PSO. The researchers in this work [15] based it on attaching the quantity of economic demand in a two-level supply chain model with a carbon tax and emission penalties [9]. Where the researcher and his colleagues were interested in developing improvement models to reduce the carbon footprint, where the relationship was found between the discrepancy in the quantity produced and the quantity of carbon emitted.

The second environmental constraint (particulate matter emissions) is a global concern for environmental monitoring and regulating particulate matter emissions of industrial systems. The Environmental Protection Agency (EPA) impose, therefore, legal penalties for those whose emissions exceed the reference limit values. The EPA defines particulate matter as "particulate pollutants," which consist of acid and chemical particles, soil particles, and dust. In this study, we are interested in Particulate Matter (PM). In the production of plants, the processed PM is discharged via stacks or pipe. This present paper proposes a solution to the planning problem with OWMR under particle matters emission constraints. In this work, we have expanded the research [10] in different directions to make it more realizable. At the beginning, we describe a logistics structure under an environmental constraint then, we consider that the main source of PM emission at the level of production and transport functions. We've developed an approach based on a metaheuristic algorithm called the binary particle swarm optimization (BPSO). This approach can be used as a resolution method to assist company managers in determining how and when to trigger production in order to satisfy a customer service rate with a minimum total cost while respecting PM emission constraints knowing that this problem is NP-hard [16].

After a brief introduction, we have described the planning problem with OWMR under cumulative emission of particulate matter constraint developed in Section 2. Then, the appropriate BPSO is provided in Section 3. The numerical experiment results are reported in Section 4. Section 5 concludes the work and suggests research opportunities and directions for further work.

Figure 1 presents an example of PMcement production process SKIKDA-Algeria.

Table 1. Literature review

Authors	Carbon Emission Constraint				Description Model	Approach
	CAP	CAP & TRADE	TAX	PENALTY		
[17]	-	-	-	-	Inventory model transportation	Dynamic programming
[7]	*	*	-	-	Single echelon inventory	EOQ
[18]	-	-	-	-	Stochastic model	Tabu search
[19]	*	*	-	-	Classical single-period model	NEWSVENDOR
[15]	-	-	*	*	Two echelon supply chain	EOQ
[10]	*	-	-	-	Multi sourcing deterministic lot-sizing problems	Dynamic programming
[20]	*	*	*	-	Single echelon inventory model	EOQ
[21-24]	*	*	*	-	Multi-item production extended	NEWSVENDOR
[25]	-	*	*	-	Dual sourcing	NEWSVENDOR
[26]	*	*	-	-	Inventory model with truck capacities	Heuristic local search algorithm
[12]	*	*	*	*	Replenishment and supplier/transportation	CPLEX
[18, 27]	*	*	-	-	Multi product single-period production model stochastic demand	Classical Newsboy model
[11]	*	*	-	*	Single period, single product inventory problem stochastic D	Classical newsboy model
[18, 27]	*	-	-	-	One plant, multiple distribution centers (DCs) and multiple retailers	Genetic algorithm
[28]	*	*	-	-	Multi (Manufacturing plant, warehouse, product) with transport mode	Cross-entropy
[29]	*	-	*	-	Multi-echelon production-inventory model with lead time	CPLEX
[30]	*	*	*	-	Single echelon inventory	EOQ
[18, 27]	-	-	*	-	Two echelon inventory (Distributors and retailers) model	
[31]	*	*	*	-	Supply chain network design model (inventory, production and transport with product, network and facility parameters	CPLEX
[32]	-	-	-	-	Stochastic capacitated lot sizing problem	CPLEX
[18, 27]	*	-	-	-	Third-party logistics providers (3PLs). multi warehouse	CPLEX
[33]	-	*	-	-	Multi-stage dynamic optimization problem	Dynamic programming
[34]	-	-	-	-	Non-stationary stockastic demand	Mixed integer linear programming
[33]	-	*	-	-	Multi-stage dynamic optimization problem	AMPL/CPLEX
[35]	-	*	-	-	Two echelon multi-product supply chain	EOQ and EPQ

Figure 1. Particle matter emissions in the cement industry in SKIKDA-Algeria

2. DEFINITION AND PROBLEM FORMULATION

2.1 Problem definition

Environment

We can define the Just-in-time logistics structure by a production unit and a distribution network (size, number and location) of the different retailers specified by a single product, as show in Figure 2.

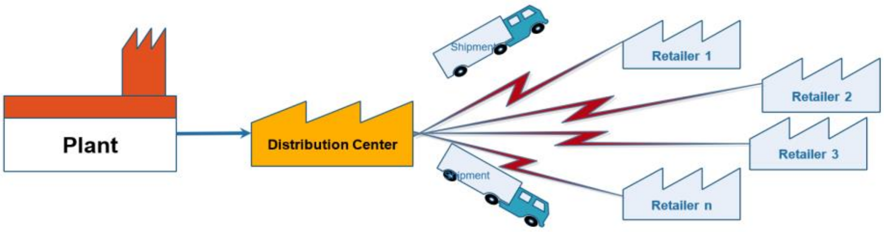

Figure 2. Structure studies

Assumptions

The main assumptions are as follows:

- The amount of the emitted PM is taken in lead time.
- Proportionality between production batches and PM emissions.
- No inventory allowed on the distribution center.
- Retailers belong the planning horizon.
- The demands are probabilistic
- The client satisfaction is a priority in each period.

Objective

Minimizing the total cost of structure logistic.

We will introduce the mathematical formulation of Mixed Integer Linear Programming (MILP) in this next part.

2.2 Problem formulation

Objectif function

$$Min\ Z = \sum_{t=1}^{T}(Production\ cos + Distribution\ Center\ cost) + \sum_{t=1}^{T}\sum_{i=1}^{NR}(Retailers\ cost) \quad (1a)$$

$$Min\ Z = \sum_{t=1}^{T}(fp_i \boldsymbol{y_t} + p_i \boldsymbol{x_t}) + (fd_t \boldsymbol{yd_t} + sd_t \boldsymbol{Id_t}) + \sum_{t=1}^{T}\sum_{i=1}^{NR}(fr_{it} \boldsymbol{yr_{it}} + sr_{it} \boldsymbol{Ir_{it}})$$

$$Min\ Z2 = \sum_{t=1}^{T}(fp_i \boldsymbol{y_t} + p_i \boldsymbol{x_t}) + (fd_t \boldsymbol{yd_t} + sd_t \boldsymbol{Id_t}) + \sum_{t=1}^{T}\sum_{i=1}^{NR}(fr_{it} \boldsymbol{yr_{it}} + sr_{it} \boldsymbol{Ir_{it}}) + \sum_{t=1}^{T}\sum_{i=1}^{NR}(ut_{it} \boldsymbol{ql_{it}})\ (1') \quad (1b)$$

$$Min\ Z = \sum_{t=1}^{T}(fp_i \boldsymbol{y_t} + p_i \boldsymbol{x_t}) + (fd_t \boldsymbol{yd_t} + sd_t \boldsymbol{Id_t}) + \sum_{t=1}^{T}\sum_{i=1}^{NR}(fr_{it} \boldsymbol{yr_{it}} + sr_{it} \boldsymbol{Ir_{it}}) + \sum_{t=1}^{T}\sum_{i=1}^{NR}(ut_{it} \boldsymbol{ql_{it}})$$

Subject to

The production capacity constraint

$$x_t \leq y_t cap_t \quad (2)$$

The inventory level of DC and retailers' constraints

$$Id_t = Id_{t-1} + x_t - \sum_{i=1}^{NR} d_{it} \quad (3)$$

$$Ir_{it} = Ir_{it-1} + ql_{it} - d_{it} \quad (4)$$

The PM emission constraint

$$\sum_{k=1}^{t}(pe_k^m - PE_k^m)\, x_k \leq 0 \quad (5)$$

$$h_t^m = h_{t-1}^m - (pe_k^m - PE_k^m) x_t \quad (6)$$

$$h_t \geq 0\ ;\ h_0 = 0 \quad (7)$$

The domain of definition of decision variables

$$x_t, Id_t, Ir_{it} \geq 0;\ intergers\ \forall\ \text{i, t, k} \quad (8)$$

The definition of decision variables

$$y_t = \begin{cases} 0 \text{ if } x_t = 0 \\ 1 \text{ Otherwise} \end{cases} \quad (9)$$

$$yd_t = \begin{cases} 0 \text{ if } Id_t = 0 \\ 1 \text{ Otherwise} \end{cases} \quad (10)$$

$$yr_{it} = \begin{cases} 0 \text{ if } Id_t = 0 \\ 1 \text{ Otherwise} \end{cases} \quad (11)$$

Table 2 presents the measurements of these particles over a 2018-2019 horizon in this company.

Table 3 explains the principle of inventory emission variable.

Table 2. Presentation of dust measurements in 2018-2019 at the cement industry in SKIKDA, Algeria

	2018		2019	
Location	**Production Tons**	**Particle Matter (Mg/Nm³)**	**Production Tons**	**Particle Matter (Mg/Nm³)**
GP120 Filter		25.67		30.92
Handle filter outlet L01		0.81		6.34
Handle filter outlet L02	1008783.84	0.78	1086120.3	3.72
L01 Chiller Bag Filter Outlet		0.68		2.16
L02 Chiller Bag Filter Outlet		1.21		1.65

In Table 3, example for cumulative emission h_t values increase until t=6, because PE_t is greater then pe_t ($PE_t > pe_t$); it means permission is sufficient for production. Till t=7 h decrease PE_t is less then pe_t ($PE_t < pe_t$), it means we need permissions from inventory emission to produce x quantity. This is what explain clearly Figure 3. In another manner:

For t=1 to T do
If $PE_t * x_t > pe_t x_t$ then
Do not need h_t
Else
Need h_t
End.

Table 3. Example for cumulative emission

t	x	pe	Emission	PE	pe-PE	x(pe-PE)	H
1	100	10	1000	15	-5	-500	500
2	120	5	600	10	-5	-600	1100
3	50	15	750	17	-2	-100	1200
4	0	17	0	20	-3	0	1200
5	250	10	2500	15	-5	-1250	2450
6	25	9	225	10	-1	-25	2475
7	40	12	480	10	2	80	2395
8	90	8	720	4	4	360	2035
9	0	14	0	8	6	0	2035
10	200	5	1000	5	0	0	2035

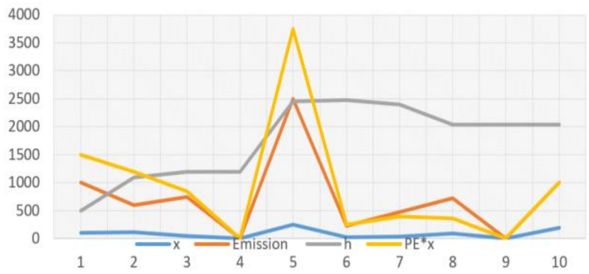

Figure 3. Cumulative emission

Another scenario presents itself, when h takes negative values; that mean in this period plant cannot produce all quantity desired because it has not permission for particle emission. It has consumed all its reserve during the previous periods. Therefore, in this case plant must reduce production to get at least zero inventory of emission and satisfy environmental constraint.

After we have defined the mathematical model in MIPL with different constraints, we will go through proposing a way to solve this problem.

3. BINARY PARTICLE SWARM OPTIMIZATION FOR PLANNING PROBLEM WITH OWMR

3.1 The basis of PSO

Particle swarm optimization (PSO) is developed by Kennedy and Eberhart, and it the main product is through consistency and competition by conveying specific information to guide the improvement process [36].

Algorithm General PSO

Begin
Initialize randomly swarm, velocity/*a set of particles
Calculate Pbest, Gbest
For i=1 to NI/*number of iterations
Calculate new velocity
Calculate new swarm
Calculate Pbest and Gbest
Seek fitness
End for
Write fitness/*the best value from all.
End

Now we adopt this algorithm to solve capacitated lot-sizing problem.

3.2 Structure of the binary PSO algorithm

Better efficiency of PSO -based search could be achieved by modifying the particle representation and its related operators to generate feasible solutions [37].

Sazvar et al. [14] proposed an integer presentation of the particle; each particle refers to the number of batch sizes ordered for each product for each period to solve a supply chain with perishable items. Boonmee and Sethanan [38] developed a new decoding representation where each particle in the swarm is separated into two parts, to solve multi-level capacitated lot-sizing and scheduling problems. The first part is the number of chicks purchased and delivered to the poultry industry in each period, and the second part is the allocation of chicks and pullets to farms.

However, Chen and Lin [39] developed a representation of complex particles encoding type is integers, while Izakian et al. [40] only encoded with binary values, which speeds up the algorithm and deals with large solution spaces.

We have designed an effective particle representation with an accelerated algorithm on the basis of the analysis of the approach adopted from the above literature. PSO simulates the movement of a group of volatile particles. It can search very large spaces of candidate solutions.

Now, we adopt this algorithm to solve capacitated lot-sizing problem.

3.2.1 Binary particle encoding

In this case, we use two particles:

(1) L_{it}: binary matrix $L_{it} = \begin{bmatrix} 1 & 0 & 0 & 1 & 0 & 1 & 0 \\ 1 & 1 & 0 & 0 & 0 & 1 & 0 \\ 1 & 0 & 0 & 0 & 1 & 1 & 1 \end{bmatrix}$

(2) y_t=[1 0 0 1 0 0 1]

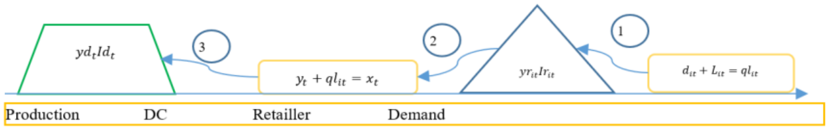

Figure 4. Way for calculation

3.2.2 Calculating fitness

To calculate z, we need all the values of decision variables $x_t, Id_t, Ir_{it}, yd_t, yr_{it}$, from particles one; such parameters are mentioned in Figure 4, which illustrates the way of calculation.

Algorithm quantity delivered

```
Begin
ql=0
   For i=1 to NR do
      For t=1 to T
        If L(i,t)=1
         ql(i;t)=d(i;t)
         k=t
        Else
      While L(i,t)=0
         ql(i;k)= ql(i;k)+d(i;t)
         t=t+1
   End for
Ir(I, t)=Ir(I,t-1)+ql(i,t)-d(i,t)
If Ir(i, t)= 0 then
     yr(i, t)=0
Else
    yr(i, t)=1
End if
```

The next step is to find the produced quantity. We should use the delivered quantity instead of the demand written in the produced quantity algorithm.

Algorithm quantity produced

```
Begin
x=0; h=0
   For t=1 to T do
        If y(t)=1
         x(t)=sum ql(i; t)
if PE(t) > pe(t) then
h=h+(PE(t)-pe(t));
end
k=t
        Else
      While y(t)=0 and x(k)≤cap(t) and p ≤ h
         x(k)=x(k)+sum ql(i,t)
         h=h+(PE(t)-pe(t));
         t=t+1
     End while
If (x(k)>cap(t) or pe(t)>PE(t) then/*test constraint capacity and CAP emission
x(k)=x(k)-sum ql(i, t)
Y(t)=1
End if
t=t-1
Id(t)=Id(t-1)+x(t)-sum ql(i, t)
End for
If Id(t)=0 then
     yd(t)=0
Else
    yd(t)=1
End if
End
```

Everything is ready to calculate fitness. The next step is to use PSO to solve the capacitated lot-sizing problems.

3.2.3 Binary PSO algorithm

(1) Generate randomly X such as

$$X(i,t,p) = \begin{bmatrix} y \\ L \end{bmatrix} = \begin{bmatrix} [1 & 0 & 0 & 1 & 0 & 0 & \mathbf{1}] \\ [1 & 0 & 0 & 1 & 0 & 1 & 0] \\ [1 & 1 & 0 & 0 & 0 & 1 & 0] \\ [1 & 0 & 0 & 0 & 1 & 1 & 1] \end{bmatrix}$$

where, i=1, i=1, t=7, p=1

(2) Generate randomly V in $[-v;\ +v]$ when Dim [X]=Dim [V]

(3) Calculate fitness $gbest$ and $pbest$ as shown in Table 4.

Table 4. Fitness values

P	Iter1	Iter2	Iter3	Iter4
1	25	20	18	16
2	40	35	25	15
3	20	19	30	25
4	60	45	20	22

(4) Next iterations to calculate the new velocity V for $V_{(i,t,p)}^{iter+1}$

Using the following equation:

$$V_{(i,t,p)}^{iter+1} = \omega V_{(i,t,p)}^{iter} + C1r1\left(pbest^{iter} - X_{(i,t,p)}^{iter}\right) + C2r2\left(gbest^{iter} - X_{(i,t,p)}^{iter}\right) \tag{12}$$

(5) Calculate new X, $X_{(i,t,p)}^{iter+1} = \begin{cases} 1 \text{ if } Sig\left(V_{(i,t,p)}^{iter+1} > r\right) \\ 0 \text{ otherwise} \end{cases}$

Such as $Sig = \frac{1}{1+e^{-V_{(i,t,p)}^{iter+1}}}$

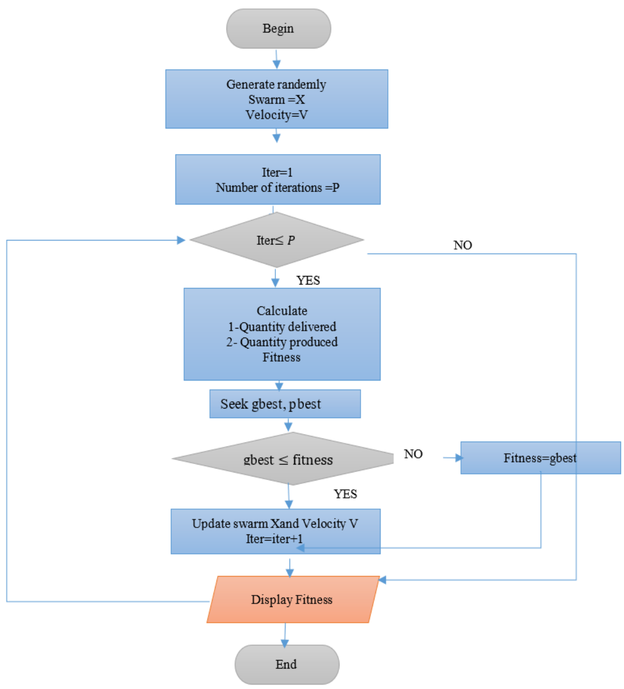

Figure 5. Framework of the proposed BPSO

In Figure 5, the detailed procedure of the Binary Particle Swarm Optimization for the planning problem with OWMR.

4. COMPUTATIONAL EXPERIMENTS

In order to investigate the performance of the proposed algorithm (BPSO), a concrete analysis of the proposed algorithm is made. The BPSO is coded on Lenovo PC with 8G RAM and 2GHz. The software is MATLAB 2013. I have run my proposed algorithm for ten times on the same instance with the same best values of the selected parameters as it is shown in Table 5 [41-43].

Table 5. The best parameters values for BPSO

Parameters	Values	Best Parameters
$\boldsymbol{\omega}$	[1,10]	1
$\boldsymbol{C1}$	[1,4]	3
$\boldsymbol{C2}$	[1,4]	3
$\boldsymbol{P}$	[50,200]	100
$\boldsymbol{V}$	[10,90]	50

The instance problems case for the planning problem with OWMR under environment (PM emission) constraint are presented as following (see Table 6):

Table 6. Instances variation for the proposed BPSO

T	NR	T	NR	T	NR
Small size		Medium size		Big size	
3,6,9,12	[2,10]	15,18,21,27	[5,25]	40,50,60,70	[30,70]

- Case 1: little size/30 instance problems/(T∈[3; 12], NR∈[2; 10])
- Case 2: middle size/30 instance problems (T∈[15; 27], NR∈[5; 25])
- Case 3: great size/30 instance problems/(T∈[40; 70], NR∈[30; 70])

Table 7 displays the computational results of our proposed BPSO. In this table, the problem instances are listed in the first column, the second PM emissions and the third columns represent the number of period and retailers respectively, the fourth and five column that refer to our algorithms are still compared with CPLEX lower bound.

For each instance, results are summarized in Table 7, in which we compare our proposed BPSO algorithms and CPLEX in terms of total cost $\boldsymbol{Z_{BPSO}}$ time and running Time(s).

- **Little size**

From Table 7 in the little size, the difference between $\boldsymbol{Z_{BPSO}}$ and $\boldsymbol{Z_{CPLEX}}$ is Err ∈[0; 0.65] s is small, when BPSO speed reaches 0.65s, it gives us solution optimal. We have also noticed a proportionality between the running time and (T, NR).

- **Middle size**

From Table 7 in the Middle size, the difference between $\boldsymbol{Z_{BPSO}}$ and $\boldsymbol{Z_{CPLEX}}$ is Err ∈[0.98; 3.29] s for an increased instance (T, NR), and the Err increases too. We have also noticed a proportionality between the running time and (T, NR).

- **Great size**

From Table 7 in Great size, the difference between $\boldsymbol{Z_{BPSO}}$ and $\boldsymbol{Z_{CPLEX}}$ is Err ∈[7.26; 11.65] s for an increased instance (T, NR) and the Err increases more as well.

$$Err = \frac{Z_{PSO} - Z_{CPLEX}}{Z_{CPLEX}}$$

The running time BPSO is better than CPLEX.

Table 7. Performance of BPSO

Instances			PM Emission PE	Pe	T	NR	T*NR	PSO Z_{PSO}	Time(s)	CPLEX Z_{CPLEX}	Time (s)	Err
	1	1	U[3,6]	U[2,5]	3	2	6	1030	27.931	1030	0.614	0
	2	2	U[3,6]	U[2,5]	3	4	12	574	61.1	575	1.343	0
	3	3	U[3,6]	U[2,5]	6	2	12	1311	54.977	1295	1.208	0.01
	4	4	U[3,6]	U[2,5]	3	6	18	2953	65.26	2954	1.434	0
	5	5	U[3,6]	U[2,5]	6	3	18	587	60.45	589	1.302	0
	6	6	U[3,6]	U[2,5]	9	2	18	3732	60.918	3589	1.339	0.04
	7	7	U[3,6]	U[2,5]	3	8	24	3831	33.709	3831	0.741	0
	8	8	U[3,6]	U[2,5]	6	4	24	3831	33.709	3794	0.741	0.01
	9	9	U[3,6]	U[2,5]	12	2	24	4982	62.244	4152	1.368	0.2
	10	10	U[3,6]	U[2,5]	3	9	27	5841	67.205	5841	1.469	0
	11	11	U[3,6]	U[2,5]	9	3	27	9653	33.835	9553	0.819	0.01
	12	12	U[3,6]	U[2,5]	3	10	30	7325	36.504	7261	0.802	0.01
	13	13	U[3,6]	U[2,5]	6	5	30	8652	33.705	8635	0.823	0
Little size	14	14	U[3,6]	U[2,5]	6	6	36	5906	130.52	5791	2.869	0.02
	15	15	U[3,6]	U[2,5]	9	4	36	5870	66.989	5755	1.472	0.02
	16	16	U[3,6]	U[2,5]	9	5	45	9565	67.301	9326	1.467	0.02
	17	17	U[3,6]	U[2,5]	6	8	48	7662	67.405	7439	1.482	0.03
	18	18	U[3,6]	U[2,5]	12	4	48	9197	70.07	7075	1.54	0.3
	19	19	U[3,6]	U[2,5]	6	9	54	9383	73.098	9122	1.6	0.03
	20	20	U[3,6]	U[2,5]	9	6	54	17012	73.086	16421	1.606	0.04
	21	21	U[3,6]	U[2,5]	6	10	60	14651	73.008	14406	1.605	0.02
	22	22	U[3,6]	U[2,5]	12	5	60	14651	73.326	14406	1.626	0.02
	23	23	U[3,6]	U[2,5]	9	8	72	11919	79.014	11572	1.737	0.03
	25	25	U[3,6]	U[2,5]	12	6	72	11700	79.313	8299	1.743	0.41
	26	26	U[3,6]	U[2,5]	15	5	75	5952	82.654	3608	1.816	0.65
	27	27	U[3,6]	U[2,5]	9	9	81	9565	82.126	9326	1.923	0.02
	28	28	U[3,6]	U[2,5]	9	10	90	21803	86.489	14536	1.901	0.5
	29	29	U[3,6]	U[2,5]	12	8	96	16971	89.284	11624	1.962	0.4
	30	30	U[3,6]	U[2,5]	12	9	108	15245	91.326	10136	1.852	0.501

	31	**31**	**U[3,4]**	**U[2,3]**	**18**	**5**	**90**	**6892**	**85,501**	**1887**	**33.879**	**2.652**
	32	32	U[3,4]	U[2,3]	21	5	105	11771	91.286	2243	35.875	2.006
	33	33	U[3,4]	U[2,3]	12	10	120	15140	97.955	9961	33.321	2.153
	34	34	U[3,4]	U[2,3]	27	5	135	9661	103.35	1281	60.732	2.271
	35	35	U[3,4]	U[2,3]	15	10	150	16887	108.212	8529	60.378	2.378
	36	36	U[3,4]	U[2,3]	18	10	180	20284	117.195	8992	65.576	2.576
	37	37	U[3,4]	U[2,3]	21	10	210	36845	129.675	7066	71.089	2.85
	38	38	U[3,4]	U[2,3]	15	15	225	40385	136.695	17949	70.004	3.004
	39	39	U[3,4]	U[2,3]	18	13	234	30254	137.025	7542	70.52	3.011
	40	40	U[3,4]	U[2,3]	18	15	270	73815	152.321	18641	73.348	3.348
	41	41	U[3,4]	U[2,3]	27	10	270	30805	152.75	4247	73.023	3.357
	43	43	U[3,4]	U[2,3]	21	13	273	73262	152.98	15478	73.828	3.735
	44	44	U[3,4]	U[2,3]	15	19	285	33585	165.25	8754	74.110	2.83
Middle size	45	45	U[3,4]	U[2,3]	15	20	300	76534	165.386	33955	74.080	3.635
	46	46	U[3,4]	U[2,3]	21	15	315	40363	160.417	6397	73.584	3.745
	47	47	U[3,4]	U[2,3]	18	19	342	76982	171.123	11548	70.365	5.66
	48	48	U[3,4]	U[2,3]	15	23	345	54576	170.502	11587	73.58	3.710
	49	49	U[3,4]	U[2,3]	18	20	360	50575	189.371	15120	44.623	4.162
	50	50	U[3,4]	U[2,3]	15	25	375	30120	196.586	8991	44.320	4.32
	51	51	U[3,4]	U[2,3]	21	19	399	77895	200.93	13254	44.523	4.887
	52	52	U[3,4]	U[2,3]	27	15	405	87628	201.76	10622	44.623	4.434
	53	53	U[3,4]	U[2,3]	18	23	414	82585	205.36	15236	49.326	4.423
	55	55	U[3,4]	U[2,3]	21	20	420	38178	213.98	5796	50.356	4.703
	56	56	U[3,4]	U[2,3]	18	25	450	56901	225.81	13376	52.963	3.25
	57	57	U[3,4]	U[2,3]	21	23	483	79852	223.52	13845	52.627	4.985
	58	58	U[3,4]	U[2,3]	27	19	513	88956	225.66	15852	52.071	4.611
	59	59	U[3,4]	U[2,3]	21	25	525	46904	227.27	9003	52.962	5.654
	60	60	U[3,4]	U[2,3]	27	20	540	43615	256.62	4714	52.987	5.64
	61	61	U[2,4]	U[1,3]	40	30	1200	180659	538.2	18530	448.5	8.75
	62	62	U[2,4]	U[1,3]	40	35	1400	338803	528.19	31459	440.158	9.77
	63	63	U[2,4]	U[1,3]	50	30	1500	435249	661.31	41217	551.092	9.56
	64	64	U[2,4]	U[1,3]	40	40	1600	227569	733.98	23015	611.65	8.89
	65	65	U[2,4]	U[1,3]	50	35	1750	515273	777.53	51766	647.942	8.95
	66	66	U[2,4]	U[1,3]	40	45	1800	178438	897.52	17402	747.933	9.25
	67	67	U[2,4]	U[1,3]	60	30	1800	334717	789.1	28152	970.593	10.89
	68	68	U[2,4]	U[1,3]	40	50	2000	186797	1006.33	22626	838.608	7.26
	69	69	U[2,4]	U[1,3]	50	40	2000	548875	950.56	55125	792.133	8.96
	70	70	U[2,4]	U[1,3]	40	52	2080	183852	973.83	19856	797.362	8.259
	71	71	U[2,4]	U[1,3]	60	35	2100	305751	953.94	29830	1173.346	9.25
	72	72	U[2,4]	U[1,3]	70	30	2100	379088	901.94	30231	2899.737	11.54
	73	73	U[2,4]	U[1,3]	40	55	2200	182973	1109.73	17895	983.408	9.224
	75	75	U[2,4]	U[1,3]	50	45	2250	664356	1109.81	57371	924.842	10.58
Great size	76	76	U[2,4]	U[1,3]	60	40	2400	365551	1119.3	36464	1376.739	9.03
	77	77	U[2,4]	U[1,3]	70	35	2450	703450	1115.66	60176	3586.847	10.69
	78	78	U[2,4]	U[1,3]	50	50	2500	776186	1300	61897	1599	11.54
	79	79	U[2,4]	U[1,3]	40	65	2600	285658	1300.86	22025	1602.258	11.656
	80	80	U[2,4]	U[1,3]	60	45	2700	399334	1301.56	36254	1600.919	10.02
	81	81	U[2,4]	U[1,3]	50	55	2750	778985	1112.63	66584	964.057	10.699
	82	82	U[2,4]	U[1,3]	70	40	2800	271554	1560	N/A	N/A	N/A
	83	83	U[2,4]	U[1,3]	60	50	3000	446246	3258.97	N/A	N/A	N/A
	84	84	U[2,4]	U[1,3]	50	65	3250	487589	1658.25	N/A	N/A	N/A
	85	85	U[2,4]	U[1,3]	60	55	3300	332557	4165.35	N/A	N/A	N/A
	86	86	U[2,4]	U[1,3]	70	55	3850	798258	1325.36	N/A	N/A	N/A
	87	87	U[2,4]	U[1,3]	60	65	3900	273854	2265.23	N/A	N/A	N/A
	88	88	U[2,4]	U[1,3]	70	60	4200	458272	2210.02	N/A	N/A	N/A
	89	89	U[2,4]	U[1,3]	70	65	4550	985025	3873.58	N/A	N/A	N/A
	90	90	U[2,4]	U[1,3]	70	70	4900	575092	4160	N/A	N/A	N/A

Figure 6 depicts the convergence behavior of BPSO for the (T=50 and NR=40) instance. This figure shows the improvement of average solution quality of this instance over the number of Iterations.

Figure 7 illustrates the running time (s) (BPSO, CPLEX). The running time is exponential linear.

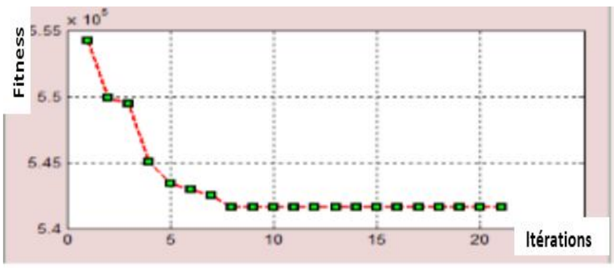

Figure 6. Decrease of cost function

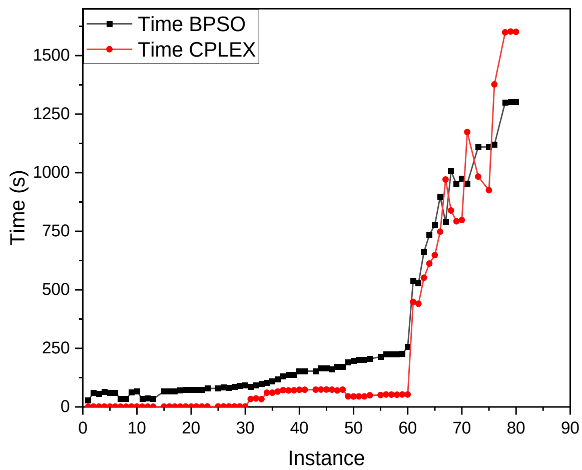

Figure 7. The running time (BPSO-CPLEX)

5. CONCLUSION

Most of the research's scholars are interested in integrating carbon emission constraint within the lot-sizing problem. In this article, we have focused on integrating hard particles different in their nature. These emissions contribute riskily to increasing air pollution, which negatively affects the environment, especially by major industrial companies, in general, and companies of construction materials and cement, in particular. In this article, we have solved a lot-sizing problem. The description model of this later is production unit and a distribution network (size, number and location) in different retailers in time under cumulative particulate matters emission constraint.

A mixed-integer programming model has been constructed the problem is NP-hard. We have developed a binary particle swarm optimization one for solving it. The BPSO approach that was proposed is powerful and delivers high-quality solutions within a short running time.

Based on the discussions and analysis of this study trend of Binary swarm intelligence optimization for solving the green lot-sizing problem,

Through this study, we have developed a specialized software that is also a decision support system Creates a decision support system to help business managers make decisions in time and space, quantity to trigger production and distribute in a sustainable environment while satisfying the customer at the lowest total cost and on the other hand respecting cumulative emissions.

We give some perspectives from the problems aspects, approaches and constraints for future works.

- The real-world constraints must be considered if we want to solve lot-sizing problem in the various industrial environments. Through considering the real-life constraints, we can put the planning results included within the theoretical research into a specific field or a specific transport and products storage as a helping tool for making decision.
- Minimizing energy consumption in transports and production are two new objectives to seek in integrating the problem of turning the vehicle and production scheduling problems with the green lot-sizing problem.
- Efficient hybrid swarm intelligence optimization with the local search is vital for solving the green lot-sizing problem.
- The models and planning strategies for multi-product and multi-objective optimization remain a challenging issue, which needs to be further studied for the lot-sizing problem.
- Comparing the results of the study with metaheuristic such as ant colonies

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NOMENCLATURE

Indices

T	Number of periods
NR	Number of retailers
t	Index of periods, t=1, 2, ..., T
i	Index of retailers, i=1, 2, ..., NR
M	Number of particulate matters
m	Index of particulate matters m=1, 2, …M

Parameters

d_{it}	Amount of demand of retailer i at the end period t
pe_k^m	PM emission quota per unitary product in
PE_k^m	Maximum unitary PM emission per period

Production

Cap_t	Total production capacity of plant during period t
p_t	Unitary cost of production
fp_t	Setup cost of production

Delivery

ut_t	delivery cost for unit of product

Holding

sd_t	Unitary holding cost for distribution center in period i
fd_t	Setup cost for distribution center in period i
sr_{it}	Unitary holding cost for retailer i in period t
fr_{it}	Setup cost for retailer i in period t

Variable decision

x_t	Quantity produced in period t
y_t	Binary variable there is or no production in period t
id_t	Inventory level in distribution center at period t
yd_t	Binary variable there is or no stock in DC in period t
ir_{it}	Inventory level for retailer i in period t
yr_{it}	Binary variable there is or no stock in retailer i in period t
qlr_{it}	Quantity delivered to retailer I at period t
X	Swarm of particles
p	Index of swarm
P	Maximum number of particles
$iter$	Index of iterations
ω	Inertia weight
$C1$, $C2$	Positive acceleration which control the influence of ***gbest*** and ***pbest*** in search process
$r1$, $r2$, r	Random variable uniform distribution