IJE TRANSACTIONS B: Application Vol. 27, No. 8, (August 2014) 1223-1232

International Journal of Engineering

Journal Homepage: www.ije.ir

RESEARCH NOTE

Three Meta-heuristic Algorithms for the Single-item Capacitated Lot-sizing Problem

E. Mehdizadeh*, A. Fatehi Kivi

Faculty of Industrial and Mechanical Engineering, Qazvin Branch, Islamic Azad University, Qazvin, Iran

PAPER INFO

Paper history:
Received 04 October 2013
Received in revised form 22 February 2014
Accepted in 06 March 2014

Keywords:
Lot-sizing
Safety stocks
Simulated Annealing
Vibration damping Optimization
Harmony Search

ABSTRACT

This paper proposes a mixed integer programming model for single-item capacitated lot-sizing problem with setup times, safety stock, demand shortages, outsourcing and inventory capacity. Due to the complexity of problem, three meta-heuristics algorithms named simulated annealing (SA), vibration damping optimization (VDO) and harmony search (HS) have been used to solve this model. Additionally, Taguchi method is conducted to calibrate the parameters of the meta-heuristics and select the optimal levels of the algorithm's performance influential factors. Computational results on a set of randomly generated instances show the efficiency of the HS against VDO and SA.

doi: 10.5829/idosi.ije.2014.27.08b.08

1. INTRODUCTION

Planning problem consists in deciding how to transform raw material into final goods as to satisfy demand at minimum cost. The lot-sizing problem (LSP) is a crucial step and well-known optimization problem in production planning in which involved time-varying demand for set of *N* items over *T* periods. It is a class of production planning problems in which the availability amounts of the production plan are always considered as decision variable. Two versions of the lot-sizing problems are capacitated and uncapacitated lot-sizing problem. The uncapacitated single-item version of the problem can be solved efficiently using dynamic programming [1]. Stadtler [2] changed the single-item uncapacited lot-sizing model considering the planning horizon theory. Aksen, et al [3] addressed a profit maximization version of the well-known Wagner–Whitin model for the deterministic single-item uncapacitated lot-sizing problem with lost sales. They proposed an $O(T^2)$ forward dynamic programming algorithm to solve the problem. Akbalik and Rapine [4] considered the uncapacitated lot sizing problem with batch delivery. Akbalik and Rapine [5] considered the single-item uncapacitated lot-sizing problem with batch delivery, focusing on the general case of time-dependent batch sizes. They showed that the problem is polynomially solvable in time $O(T^3)$, where T denotes the number of periods of the horizon.

In industrial applications, several factors may sophisticate making best decisions. For instance, capacity can be led to impossibility to satisfy demand. For this reason, the capacitated lot-sizing problem and its variations have received a lot of attention from academic researchers. Montgomery, et al. [6] Presented several single-echelon, single-item, static demand inventory models for situations in which, during the stock out period, a fraction *b* of the demand is backordered and the remaining fraction 1 - *b* is lost forever. On the other hand, backlogging, safety stocks and limited outsourcing are three complicating constraints to reach desired solutions in lot-sizing problem.

In addition, both deterministic and stochastic demands are considered. He considered only part of the fixed costs associated with decision making in improving programming in order to develop a model

*Corresponding Author's Email: emehdi@qiau.ac.ir (Esmaeil Mehdizadeh)

Please cite this article as: E. Mehdizadeh, A. Fatehi Kivi, Three Meta-heuristic Algorithms for the Single-Item Capacitated Lot-sizing Problem. International Journal of Engineering (IJE) Transactions B: Applications Vol. 27, No. 8, (2014): 1223-1232

which can cover periods beyond the planning horizon and can be applicable to a wide range of decision making models. He also proved that if the periods in the planning horizon are not fixed, dynamic optimum methods will not function non-optimally. Abad [7] considered the problem of determining the optimal price and lot-size for a reseller. He assumed that demand can be backlogged and that the selling price is constant within the inventory cycle. Karimi, et al. [8] considered single level lot-sizing problems, their variants and solution approaches. Berretta and Rodrigues [9] developed methods based on evolutionary metaheuristics to solve a complex problem in production planning, the multi-stage lot-sizing problem with capacity constraints. Brahimi, et al. [10] presented four different mathematical programming formulations of the Single-item lot-sizing problems. Robinson et al. [11] updates a 1988 review of the coordinated lot-sizing problem and complements reviews on the single-item lot-sizing problem and the capacitated lot-sizing problem. Akbalik and Penz [12] studied a special case of the single-item capacitated lot-sizing problem, where alternative machines are used for the production of a single-item. They proposed an exact pseudo-polynomial dynamic programming algorithm which makes it NP-hard in the ordinary sense. They also gave three mixed integer linear programming (MILP) formulations that we have found in the literature for the simplest case of the problem. Akbalik and Pochet [13] presented a new class of valid inequalities for the single-item capacitated lot-sizing problem with step-wise production costs. They proposed a cutting plane algorithm for different classes of valid inequalities introduced. Wang, et al. [14] addressed the single-item, dynamic lot-sizing problem for systems with remanufacturing and outsourcing. They proposed a dynamic programming approach to derive the optimal solution in the case of large quantities of returned product. Mikhail, et al. [15] proposed a straightforward $O(nLogn)$ time algorithm for the single-item capacitated lot-sizing problem with linear costs and no backlogging.

The capacitated lot-sizing problems encountered in real-life situations are generally intractable due to a number of practical constraints. The decision maker has to find a good feasible solution in a reasonable execution time rather than an optimal one. Tang [16] provides a brief presentation of simulated annealing techniques and their application in lot-sizing problems. Mokhtari and Kianfar [17] considered a production system in which the orders of several customers are produced in a single batch. The problem was to decide on batch size, due date of batch and lead time so that relevant costs are minimized. Production flow times are probabilistic which follow a probability distribution. The proposed model is solved using real-coded genetic algorithms. Jenabi et al. [18] considered the economic lot and delivery scheduling problem in a two-echelon supply chains, where a single supplier produces multiple components on a flexible flow line and delivers them directly to an assembly facility. They developed a new mixed zero-one nonlinear mathematical model for the problem. Two meta-heuristic algorithms (HGA and SA) were proposed. Piperagkas, et al. [19] investigated the dynamic lot-size problem under stochastic and non-stationary demand over the planning horizon. They used three popular heuristic methods from the fields of evolutionary computation and swarm intelligence, namely particle swarm optimization, differential evolution and harmony search for solve the model. Chu, et al. [20] addressed a real-life production planning problem arising in a manufacturer of luxury goods. The problem modeled as a single-item dynamic lot-sizing model with backlogging, outsourcing and inventory capacity. They showed that this problem can be solved in $O(T^4 logT)$ time where T is the number of periods in the planning horizon.

The main contribution of this paper is twofold. First, we develop a single-item capacitated lot-sizing model with demand shortage, safety stock, limited outsourcing and several manners for produce. Then, we use simulated annealing, vibration damping optimization and harmony search algorithms to solve the problem and compared them together.

The remaining of this paper is organized as follows: Section 2 describes a MIP formulation of the single-item capacitated lot-sizing problem with backlogging, safety stocks and limited outsourcing.

The solution approaches for solving the proposed model introduced in Section 3. The Taguchi method for tuning the parameters and computational experiments presented in Section 4. The conclusions and suggestions for future studies are included in Section 5.

2. PROBLEM FORMULATION

The single-item capacitated lot-sizing problem with backlogging, safety stocks and limited outsourcing is a production planning problem in which there is a time-varying demand for an item over T periods. In this section, we present a MIP formulation of the problem. First, the problem assumptions, parameters, and decision variables have thoroughly been introduced and then the proposed model has been defined.

2. 1. Assumptions

Before the formulation is presented, the following assumptions are made on the problem:

- The demand is considered deterministic.
- Shortage is backlogged.
- Shortage and inventory costs must be taken into consideration at the end.

- Raw material resource with given capacities are considered.
- The quantity of inventory and shortage at the beginning of the planning horizon is zero.
- The quantity of inventory and shortage at the end of the planning horizon is zero.

2. 2. Parameters

T: Number of periods in the planning horizon, t=1, …, T.

J: Number of production manner, j=1, …, J

r_t: The selling price of each unit in the period t.

C_{jt}: The production cost of each unit in the period t through the manner j.

A_{jt}: The setup cost of the production in the period t through the manner j.

h_t^+: The unit holding cost in the period t.

h_t^-: Unitary safety stock deficit cost in period t.

d_t: The demand in the period t.

L_t: The quantity of the safety stock of product in the period t.

∂_t: Unitary shortage cost in period t.

B_{kt}: The capacity of the K source at hand in the period t.

a_k: The quantity of K source used by each unit of the product.

f_{jk}: The quantity of wasted K source produced through the manner j.

g_t: Unit out-sourcing cost at period t.

v: Space need for per unit.

j_t: The total available space in period t.

2. 3. Decision Variables

X_{jt}: Production quantity in the period *t* through the manner *j*.

y_{jt}: Binary variable; 1 if the produced in the period *t* through the manner *j*, otherwise $y_{jt} = 0$.

U_t: Out-sourcing level at period t.

I_t^-: The quantity of shortage in the period *t*

S_t^+: The quantity of overstock deficit in the period *t*.

S_t^-: The quantity of safety stock deficit in the period *t*

2. 4. The Proposed Model

$$MaxZ = \sum_{t=1}^{T}\left(r_t(\sum_{j=1}^{J} X_{jt} + U_t) - \sum_{j=1}^{J}(C_{jt}X_{jt} - A_{jt}y_{jt}) - \partial_t I_t^- - h_t^+ S_t^+ - h_t^- S_t^- - g_t U_t \right) \quad (1)$$

Subject to:

$$S_{t-1}^+ - S_{t-1}^- - I_{t-1}^- + I_t^- + \sum_{j=1}^{J} X_{jt} + U_t = S_t^+ - S_t^- + d_t + L_t - L_{t-1} \quad \forall \quad t = 1, 2, ..., T \quad (2)$$

$$S_T^+ = 0 \quad (3)$$

$$I_T^- = 0 \quad (4)$$

$$\sum_{j=1}^{J}\left(a_k X_{jt} + f_{jk} y_{jt} \right) \le B_{kt} \quad \forall \quad k = 1, 2, ..., K, \quad t = 1, 2, ..., T \quad (5)$$

$$X_{jt} \le M_t y_{jt} \quad \forall \quad j = 1, 2, ..., J \quad t = 1, 2, ..., T \quad (6)$$

$$I_t^- \le d_t \quad \forall \quad t = 1, 2, ..., T - 1 \quad (7)$$

$$S_t^- \le L_t \quad \forall \quad t = 1, 2, ..., T \quad (8)$$

$$0 \le U_t \le I_{t-1}^- + S_{t-1}^- + d_t + L_t \quad \forall \quad t = 1, 2, ..., T \quad (9)$$

$$v(\sum_{j=1}^{J} X_{jt} + U_t) \le j_t \quad \forall \quad t = 1, 2, ..., T \quad (10)$$

$$y_{jt} \in \{0,1\} \quad \forall \quad j = 1, 2, ..., J \quad , \quad t = 1, 2, ..., T \quad (11)$$

$$X_{jt}, I_t^-, S_t^-, S_t^+ \ge 0 \quad \forall \quad j = 1, 2, ..., J \quad , \quad t = 1, 2, ...T \quad (12)$$

The objective function (1) shows difference between selling price with the total cost. Constraints (2) are the inventory flow conservation equations through the planning horizon. Constraints 3 and 4 define respectively, the demand shortage and the safety stock deficit for item at end period is zero. Constraints 5 are the capacity constraints; the overall consumption must remain lower than or equal to the available capacity. If we produce an item at period *t*, then constraints 6 impose that the quantity produced must not exceed a maximum production level M_t. M_t could beset to the minimum between the total demand requirement for item on section [*t*, *T*] of the horizon and the highest quantity of item that could be produced regarding the capacity constraints, then M_t can be show as Equation (13). Constraints 7 and 8 define upper bounds on, respectively, the demand shortage and the safety stock deficit for item in period *t*. Constraints 9 ensure that outsourcing level U_t at period t is nonnegative and cannot exceed the sum of the demand, safety stock of period t and the quantity backlogged, safety stock deficit from previous periods. Constraints 10 are the maximum space available for storage of items in excess.

Constraints 11 and 12 characterize y_{jt} is a binary variable and the variable's domains: $X_{jt}, I_t^-, S_t^-, S_t^+$ are non-negative for $j \in$ J and $t \in$ T.

$$M_t = Min\left(\frac{B_{kt} - f_{jk}}{a_k}, \sum_{t=1}^{T} d_t\right) \quad (13)$$

3. SOLUTION APPROACHES

3. 1. Simulated Annealing Algorithm Simulated annealing (SA) was initially presented by Kirkpatrick, et al. [21]. The SA methodology draws its analogy from the annealing process of solids. This analogy can be used in combinatorial optimization in which the state of solid corresponds to the feasible solution. The energy at each state also corresponds to the improvement in the objective function and the minimum energy state will be the optimal solution. In this paper, we used simple SA algorithm which its pseudo-code is shown in Figure 1.

Two important issues that need to be defined when adopting this general algorithm to a specific problem are the procedures to generate both initial solution and neighboring solutions.

3. 1. 1. Representation Schema To design simulated annealing optimization algorithm for mentioned problem, a suitable representation scheme that shows the solution characteristics is needed. In this paper, the general structure of the solution representation performed for running the simulated annealing for four periods with two production manners is shown in Figure 2.

```
Select an initial solution, X0
Xbest = X0, X = X0
While (T0 > Tf) Do
  S = 0
    While (S < L) Do
      Generate solution Xn in the neighborhood of X,
        ΔC = C(Xn) − C(X)
        If ΔC ≤ 0 then
         Xbest = Xn
        Else
         Generate y → U(0,1) Randomly
        If r < 1 − e^(−ΔC/T0) then
         X = Xn
        End if
  S = S + 1
     End While
End While
T0 = α × T0
End While
```

Figure 1. Pseudo-code of the SA algorithm

Y_{11}	Y_{21}	Y_{12}	Y_{22}	Y_{13}	Y_{23}	Y_{14}	Y_{24}
0	1	1	0	1	0	0	1

Figure 2. Solution representation.

1	0	0	1	0	1	1	0

⇩

1	0	1	1	0	1	1	0

Figure 3. An example of the neighborhood structure

```
t = 0, A = A0
Select an initial solution, X0
Xbest = X0
While (t < tmax) Do
 N = 0
  While (N < Lmax) Do
   Select a move randomly and run over Xn as:
ΔE = E(Xnew) − E(Xlast)
   If ΔE < 0 then
    Xbest = Xnew And Xn = Xnew
   Else
    Generate r → U[0,1]
     If r < 1 − e^(−At^2/2s^2) then
      Xn = Xnew
     End if
 N = N + 1
  End While
At = A0 e^(−gt/2)
t = t + 1
End While
```

Figure 4. Pseudo-code of the VDO algorithm

3. 1. 2. Neighborhood Scheme At each temperature level a search process is applied to explore the neighborhoods of the current solution. In this paper, we use mutation scheme. Figure 3 illustrates this operation on the four periods with two production manners.

3. 2. Vibration Damping Optimization Recently, a new heuristic optimization technique based on the concept of the vibration damping in mechanical vibration was introduced by Mehdizadeh and Tavakkoli-Moghaddam [22] named vibration damping optimization (VDO) algorithm. They utilized the algorithm to solve parallel machine scheduling problem. In this paper, we used simple VDO algorithm which its pseudo-code is illustrated in the Figure 4.

3. 3. Harmony Search Algorithms Harmony search (HS) is a new heuristic method that mimics the improvisation of music players. HS was proposed by Geem et al. [23]. Inspiration was drawn from musical performance processes that occur when a musician searches for a better state of harmony, improvising the instrument pitches towards a better aesthetic outcome. The HS algorithm imposes fewer mathematical requirements and does not require specific initial value settings of the decision variables [24]. The pseudo-code of applied HS algorithm for the problem is shown in Figure 5.

4. COMPUTATIONAL RESULTS

In this paper, all tests are conducted on a notbook with Intel Core i5 Processor 2.53 GHz and 4 GB of RAM. The proposed algorithms namely SA, VDO and HS are coded in Visual Basic 2000.

4. 1. Parameter Calibration

Appropriate design of parameters has significant impact on efficiency of meta-heuristics. In this paper, the Taguchi method applied to calibrate the parameters of the proposed methods namely SA, VDO and HS algorithms. The Taguchi method was developed by Taguchi [25]. This method is based on maximizing performance measures called signal-to-noise ratios in order to find the optimized levels of the effective factors in the experiments. The S/N ratio refers to the mean-square deviation of the objective function that minimizes the mean and variance of quality characteristics to make them closer to the expected values. For the factors that have significant impact on S/N ratio, the highest S/N ratio provides the optimum level for that factor. As mentioned before, the purpose of Taguchi method is to maximize the S/N ratio. In this subsection, the parameters for experimental analysis are determined. Table 1 lists different levels of the factors for SA, VDO and HS. In this paper, according to the levels and the number of the factors, the Taguchi method L_9 is used for the adjustment of the parameters.

Figures 6, 7 and 8 show S/N ratios. According to these figures 1000, 40, 0.99, 20, 0.1, 1000, 0.1, 0.7 and 150 are the optimal level of the factors T_0, L, α, A_0, g , l_{max}, PAR, HMCR and STOP.

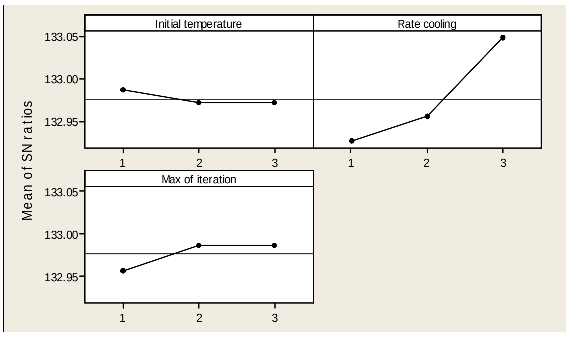

Figure 6. The SN ratios for Simulated Annealing

Define HS parameters: HMS, HMCR, PAR and STOP Criteria
$_L x_i$: Lower Bound
$_U x_i$: Upper Bound
t = 0
HMS: Harmony Memory Size = 40
Generate initialize Harmony Memory (for j = 1 to HMS)
Evaluated $f(x'_j)$
Improvise Harmony Memory
While (i < Stop Criteria)
  If (rand [0, 1] < HMCR)
    $x'_i = x'_j$, where x'_j is a random from $\{1, 2, .., HMS\}$
    If (rand [0, 1] < PAR)
      $x'_i = x'_j$, where x'_j is a random from $x'_j = rand[_L x_i, _U x_i]$
    End if
  Else
    $x'_i = 0$
  End if
Evaluated $f(x'_i)$
Accept the new harmonic (solutions) if better
i = i + 1
End while
Find the current best estimates

Figure 5. Pseudo-code of the HS algorithm

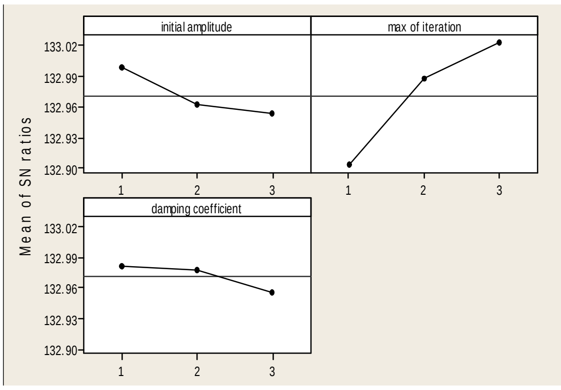

Figure 7. The SN ratios for Vibration Damping

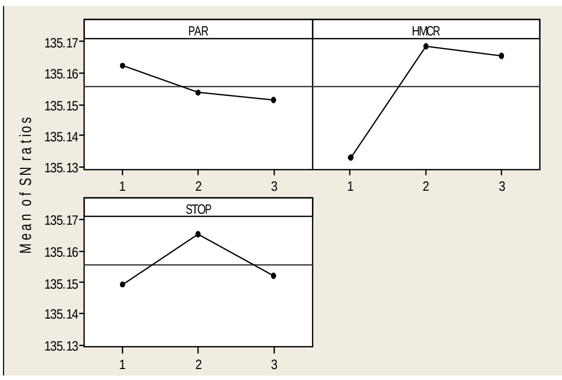

Figure 8. The SN ratios for Harmony Search

TABLE 1. Factors and their levels

Factor	Algorithm	Notation	Level	Value
Initial temperature		T_0	3	1000, 1200, 1500
Rate cooling	SA	a	3	0.9, 0.95, 0.99
Number of iteration at each temperature		L	3	30, 40, 50
Initial amplitude		A_0	3	20, 30, 40
Damping coefficient	VDO	g	3	0.1, 0.01, 0.9
Max of iteration at each amplitude		l_{max}	3	600, 800, 1000
Pitch-adjusting rate		PAR	3	0.1, 0.2, 0.3
Harmony memory considering rate	HS	HMCR	3	0.4, 0.7, 0.9
Stopping criteria		STOP	3	100, 150, 200

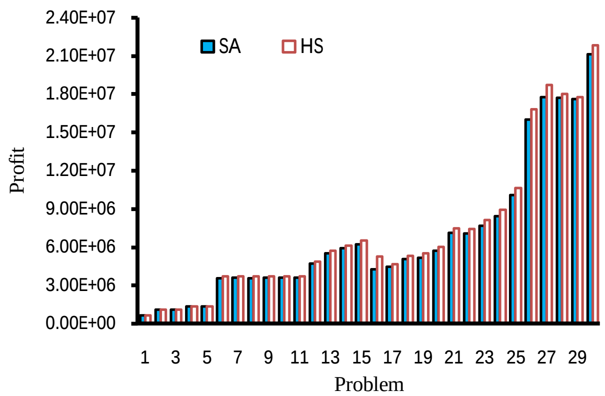

Figure 9. Comparison between solution quality of the HS and SA

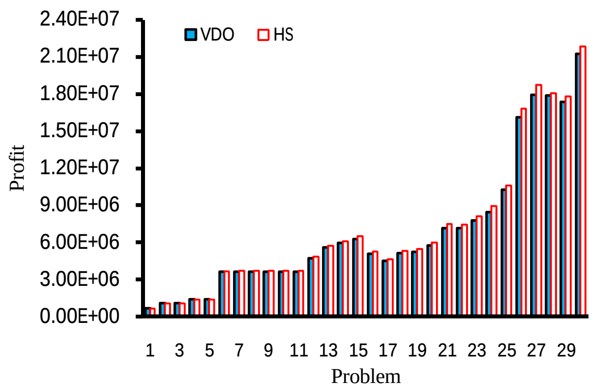

Figure 10. Comparison between solution quality of the HS and VDO

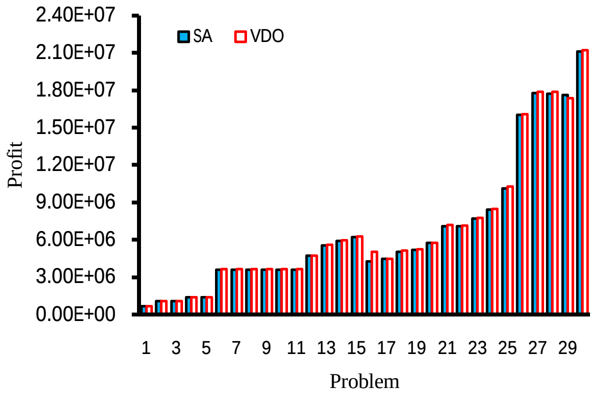

Figure 11. Comparison between solution quality of the SA and VDO

4. 2. Computational Results Computational experiments are conducted to validate and verify the behavior and the performance of the meta-heuristic algorithms employed to solve the considered single-item capacitated lot-sizing problem with backlogging, safety stocks and limited outsourcing. We try to test the performance of the SA, VDO and HS in finding good quality solutions in reasonable time for the problem. For this purpose, 30 problems with different sizes are generated. These test problems are classified into three classes: small size, medium size and large size.

The number of manners and periods has the most impact on problem hardness. The proposed model coded with Lingo (ver.8) software using for solving the instances. The approaches are implemented to solve each instance in five times to obtain more reliable data. The best results are recorded as a measure for the related problem. Table 2 shows details of computational results obtained by solution methods for all test problems. The results of running SA, VDO and HS are compared with the optimal solution of the instances, obtained from Lingo software, in row 1 to 12 of Table 2.

The presented statistical analysis (the variance analysis outcome) were reported for problems with small, medium, and large dimensions, in Tables 3, 4 and 5. According to the values of the survey (or *P-Value*), we can reach to the conclusion that the SA, VDO and HS can find good quality solutions for all test problems because deference between solutions are small. Thus, we cannot chose the better algorithm using ANOVA related.

In addition, Figure 9 depicts comparison between solution quality of the SA and HS of the instances. Figure 10 depicts comparison between solution quality of the VDO and HS of the instances. Figure 11 depicts comparison between solution quality of the SA and VDO of the instances. A general review of the results in Table 2 and Figures 9, 10 and 11 is:

- The HS can find optimal solutions for small size problems.
- The HS can find good quality solutions for all size problems.
- The objective values obtained by HS are equals to Lingo and also is better from SA and VDO results for all test problems.
- The SA, VDO and HS algorithm can solve all the test problems.
- The objective values obtained by SA and VDO are closes to each other.
- For small size test problems, SA and VDO have relatively the same results with other methods. However, its results will be worse when the problem size increases.

TABLE 2. Details of computational results for all test problems.

No	Class	Manner	Period	Objective Value			
				Lingo	SA	VDO	HS
1	Small size	2	3	649942	649942	649942	649942
2		2	5	1102440	1102440	1102440	1102440
3		3	5	1104431	1104431	1104431	1104431
4		2	6	1377965	1377965	1377965	1377965
5		3	6	1379956	1379956	1379956	1379956
6		2	12	3694085	3572083	3625962	3694085
7		3	12	3700067	3608101	3631946	3700067
8		5	12	3712166	3578066	3644034	3712166
9		6	12	3716193	3597074	3648073	3716193
10		7	12	3719184	3600065	3651065	3719184
11		8	12	3721084	3602117	3652965	3721084
12		8	16	4859594	4712929	4741940	4859594
13	Medium	8	19	-----	5538202	5576241	5747873
14		8	20	-----	5911039	5961406	6120959
15		8	21	-----	6240550	6280122	6526471
16		9	25	-----	4253801	5059248	5259494
17		10	27	-----	4476100	4485080	4646819
18		10	30	-----	5055512	5147102	5311007
19	Large	12	32	-----	5172084	5238303	5507910
20		14	34	-----	5738800	5743676	6011928
21		16	42	-----	7113985	7171750	7480750
22		18	42	-----	7083820	7132975	7444332
23		21	45	-----	7705170[a]	7771251[a]	8127934
24		21	50	-----	8410540[a]	8467926[a]	8938980[a]
25		21	60	-----	10115393[a]	10285712[a]	10619919[a]
26		21	90	-----	16029522[a]	16102554[a]	16822141[a]
27		21	100	-----	17792497[a]	17909685[a]	18719969[a]
28		50	100	-----	17706936[a]	17879986[a]	18037264[a]
29		60	100	-----	17617248[a]	17377757[a]	17782668[a]
30		60	120	-----	21123581[a]	21227656[a]	21818226[a]

— Means that a feasible solution has not been found after 3600 s of computing time.

[a] Means that finding the optimum solution requires more than 3600 s and the objective value at this time has been recorded.

$C_{jt} \in [60,85]; A_{jt} \in [20000,30000]; d_t \in [1,10]; r_t \in [45000,70000]; L_t \in [1,4];$

$\partial_t \in [14,19]; h_t^- \in [12,16]; h_t^+ \in [7,10]; g_t \in [30000,45000]; V = 1; j_t = 20; B_{kt} = 12$

TABLE 3. Analysis of variance for test problems with small size

Source	DF	SS	MS	F	P
Small-size	2	30801819025	15400909512	0.01	0.992
Error	33	6.74642E+13	2.04437E+12		
Total	35	6.74950E+13			

TABLE 4. Analysis of variance for test problems with medium size

Source	DF	SS	MS	F	P
Medium-size	2	3.80847E+11	1.90424E+11	0.38	0.691
Error	15	7.52589E+12	5.01726E+11		
Total	17	7.90674E+12			

TABLE 5. Analysis of variance for test problems with large size

Source	DF	SS	MS	F	P
Medium-size	2	1.61209E+12	8.06046E+11	0.02	0.976
Error	33	1.10997E+15	3.36356E+13		
Total	35	1.11159E+15			

5. CONCLUSION

In this paper, we propose a mathematical formulation of a new single-item capacitated lot-sizing problem with backlogging, safety stocks and limited outsourcing. This formulation takes into account several industrial constraints such as shortage costs, safety stock deficit costs and limited outsourcing. Due to the complexity of the problem, three meta-heuristic algorithms are used to solve problem instances. Additionally, an extensive parameter setting with performing the Taguchi method is conducted for selecting the optimal levels of the factors that effect on algorithm's performance. Computational results on a set of randomly generated instances showed the efficiency of the HS against VDO and SA algorithms.

One straightforward opportunity for future research is extending the assumption of the proposed model for including real conditions of production systems such as limited inventory, fuzzy demands and etc. In addition, a new heuristic or meta-heuristic to construct better feasible solutions can be developed.

6. REFERENCES

1. Wagner, H.M. and Whitin, T.M., "Dynamic version of the economic lot size model", ***Management science***, Vol. 5, No. 1, (1958), 89-96.
2. Stadtler, H., "Improved rolling schedules for the dynamic single-level lot-sizing problem", ***Management Science***, Vol .46 ,No. 2, (2000), 318-326.
3. Aksen, D., Altınkemer, K. and Chand, S., "The single-item lot-sizing problem with immediate lost sales", ***European Journal of Operational Research***, Vol. 147, No. 3, (2003), 558-566.
4. Akbalik, A. and Rapine, C., "Polynomial time algorithms for the constant capacitated single-item lot sizing problem with stepwise production cost", ***Operations Research Letters***, Vol. 40, No. 5, (2012), 390-397.
5. Akbalik, A. and Rapine, C., "The single item uncapacitated lot-sizing problem with time-dependent batch sizes: Np-hard and polynomial cases", ***European Journal of Operational Research***, Vol. 229, No. 2, (2013), 353-363.
6. Montgomery, D.C., Bazaraa, M. and Keswani, A.K., "Inventory models with a mixture of backorders and lost sales ,"***Naval Research Logistics Quarterly***, Vol. 20, No. 2, (1973), 255-263.
7. Abad, P.L., "Optimal price and order size for a reseller under partial backordering", ***Computers & Operations Research***, Vol. 28, No. 1, (2001), 53-65.
8. Karimi, B., Fatemi Ghomi, S .and Wilson, J., "The capacitated lot sizing problem: A review of models and algorithms", ***Omega***, Vol. 31, No. 5, (2003), 365-378.
9. Berretta, R. and Rodrigues, L.F., "A memetic algorithm for a multistage capacitated lot-sizing problem", ***International Journal of Production Economics***, Vol. 87, No. 1, (2004), 67-81.
10. Brahimi, N., Dauzere-Peres, S., Najid, N.M. and Nordli, A., "Single item lot sizing problems", ***European Journal of Operational Research***, Vol. 168, No. 1, (2006), 1-16.
11. Robinson, P ,.Narayanan, A. and Sahin, F., "Coordinated deterministic dynamic demand lot-sizing problem: A review of models and algorithms", ***Omega***, Vol. 37, No. 1, (2009), 3-15.
12. Akbalik, A. and Penz, B., "Exact methods for single-item capacitated lot sizing problem with alternative machines and piece-wise linear production costs", ***International Journal of Production Economics***, Vol. 119, No. 2, (2009), 367-379.
13. Akbalik, A. and Pochet, Y., "Valid inequalities for the single-item capacitated lot sizing problem with step-wise costs", ***European Journal of Operational Research***, Vol. 198, No. 2, (2009), 412-434.
14. Wang, N., He, Z., Sun, J., Xie, H. and Shi, W., "A single-item uncapacitated lot-sizing problem with remanufacturing and outsourcing", ***Procedia Engineering***, Vol. 15, No., (2011), 5170-5178.
15. Kovalyov, M.Y. and Pesch, E., "An algorithm for a single-item capacitated lot-sizing problem with linear costs and no backlogging", ***International Journal of Production Research***, Vol., No. ahead-of-print, (2013) 4-1.
16. Tang, O., "Simulated annealing in lot sizing problems", ***International Journal of Production Economics***, Vol. 88, No. 2, (2004), 173-181.
17. Mokhtari, G. and Kianfar, F., "Simultaneous due date assignment and lot sizing with uncertain flow times ," ***International Journal of Engineering Transactions A Basics***, Vol. 20, No. 3, (2007), 263.
18. Jenabi, M., Ghomi, S.F. and Torabi, S., "Finite horizon economic lot and delivery scheduling problem: Flexible flow lines with unrelated parallel machines and sequence dependent setups", ***International Journal of Engineering***, Vol. 21, (2008), 143-158.
19. Piperagkas, G.S., Konstantaras, I., Skouri, K. and Parsopoulos, K.E., "Solving the stochastic dynamic lot-sizing problem through nature-inspired heuristics", ***Computers & Operations Research***, Vol. 39, No. 7, (2012), 1555-1565.

20. Chu, C., Chu, F., Zhong, J. and Yang, S., "A polynomial algorithm for a lot-sizing problem with backlogging, outsourcing and limited inventory", ***Computers & Industrial Engineering***, Vol. 64, No. 1, (2013), 200-210.

21. Brooks, S. and Morgan, B., "Optimization using simulated annealing", ***The Statistician***, Vol., No., (1995), 241-257.

22. Mehdizadeh, E. and Tavakkoli-Moghaddam, R., "Vibration damping optimization algorithm for an identical parallel machine scheduling problem", in Proceeding of the 2nd International Conference of Iranian Operations Research Society. (2009), 20-22.

23. Geem, Z.W., Kim, J.H. and Loganathan, G., "A new heuristic optimization algorithm: Harmony search", ***Simulation***, Vol. 76, No. 2, (2001), 60-68.

24. Yadav, P., Kumar, R., Panda, S.K. and Chang, C., "An intelligent tuned harmony search algorithm for optimisation", ***Information Sciences***, Vol. 196, No., (2012), 47-72.

25. Taguchi, G., Chowdhury, S. and Taguchi, S., "Robust engineering, McGraw-Hill Professional, (2000).

Three Meta-heuristic Algorithms for the Single-item Capacitated Lot-sizing Problem

RESEARCH NOTE

E. Mehdizadeh, A. Fatehi Kivi

Faculty of Industrial and Mechanical Engineering, Qazvin Branch, Islamic Azad University, Qazvin, Iran

PAPER INFO

Paper history:
Received 04 October 2013
Received in revised form 22 February 2014
Accepted in 06 March 2014

Keywords:
Lot-sizing
Safety stocks
Simulated Annealing
Vibration damping Optimization
Harmony Search

چکیده

در این مقاله یک مدل عدد صحیح مختلط برای مسئله تعیین اندازه سفارش تک محصولی با در نظر گرفتن محدودیت ظرفیت، زمان‌های راه‌اندازی، موجودی اطمینان، کمبود، برونسپاری و فضای انبار ارائه می شود. با توجه به پیچیدگی مسئله سه الگوریتم فرا ابتکاری شبیه سازی تبرید، بهینه سازی میرایی ارتعاش و جستجوی هارمونی برای حل مدل ارائه شده به کار گرفته می‌شوند. همچنین از روش تاگوچی به منظور تنظیم پارامترهای الگوریتم‌های فرا ابتکاری و انتخاب سطوح بهینه آن‌ها استفاده می‌شود. نتایج محاسباتی از حل مثال های عددی که به صورت تصادفی تولید شده‌اند، نشان می‌دهند که الگوریتم جستجوی هارمونی در مقایسه با میرایی ارتعاش و تبرید شبیه‌سازی شده عملکرد بهتری دارد.

doi: *10.5829/idosi.ije.2014.27.08b.08*