Optimal Multi-Period Supplier Selection and Order Allocation in a Multi-Product Supply Chain incorporating Customer Flexibility

K.L.Mak and L.X. Cui

***Abstract*—Efficient and effective supplier selection and order allocation are important issues to be considered for designing flexible and highly competitive supply chains which maximize the manufacturer's total profit and ensure stable material flows. This paper proposes a novel methodology for solving an integrated supplier selection and order allocation problem that arises in the design of a multi-product supply chain, with particular reference to the influence of customer flexibility. A new mixed integer programming model incorporating the characteristics of the problem is developed to assist the manufacturer in the decision making processes. Due to the complexity and the NP-Hard nature of the proposed model, a novel hybrid algorithm based on the strengths of constraint programming (CP) and simulated annealing (SA) is developed to solve this challenging problem. The performance of the proposed algorithm is tested with a set of randomly generated test problems. Comparison with the computational results obtained by ILOG OPL clearly shows that the hybrid algorithm can locate profit-effective solutions with less computational efforts.**

***Index Terms*—Constraint programming, customer flexibility, simulated annealing, supplier selection, order allocation**

I. Introduction

With increasing product variety and escalating demand volatility, maintaining an efficient and flexible supply chain has become more critical for most enterprises. In addition, it has been observed that customers are often indifferent to certain product specifications and are often willing to accept less desirable products given certain price discounts [7]. This flexible customer behavior brings additional degree of freedom in promising customer orders and arranging available production resources. Indeed, the purpose of achieving high service level and low manufacturing cost in such dynamic supply chain environment imposes a major challenge in the order commitment process, which mainly consists of supplier selection and order allocation problems.

In this connection, this paper takes a new perspective to tackle the challenge of matching various customer requirements and available production resources in a multi-product supply chain by integrating customer flexibility into the order commitment process. The objective is to propose a novel methodology to assist the manufacturer in deciding the production quantities of all the product variants and the corresponding order allocations among selected suppliers. A new mathematic model in the form of a mixed integer programming (MIP) model is firstly developed to represent the basic characteristics of the research problem.

Constraint programming (CP) [2] is a powerful programming technique for solving large combinatorial problems. Its success has been demonstrated in solving large scale problems such as job shop scheduling problems, graph coloring problems. By efficient propagation and backtracking methods, the search space can be drastically reduced and feasible solutions can be obtained very quickly. However, the capability of CP in locating the global optimal solutions is inferior as compared to other meta-heuristic algorithms, such as simulated annealing, genetic algorithms, etc.

On the other hand, simulated annealing [6], a generic probabilistic meta-heuristic based on the manner in which liquids freeze or metals re-crystallize in the process of annealing, has been widely accepted and employed for global optimization problems due to its solution quality. The major shortcoming of simulated annealing, however, is the huge computational time required due to lack of good initial solutions and to its sequential nature of slow annealing process within the large solution space.

To solve the proposed problem, which is NP-hard by nature, a novel hybrid algorithm based on the strengths of both constraint programming technique and the simulated annealing algorithm is developed. A good feasible solution is firstly obtained quickly by constraint programming. Then simulated annealing is used to guide the search path to find the optimal solution. Unlike the traditional SA, in which the neighborhood solutions are obtained using local search methods, in the proposed hybrid algorithm, the neighborhood solutions are obtained using the constraint programming approach. The performance of the algorithm is further improved by memorizing the useful information which causes the infeasible solutions, thus reducing the solution space drastically.

The rest of this paper is organized as follows: Section 2 describes the problem scenario under investigation and presents the formulation of the mathematical model. The newly developed hybrid CP-SA algorithm is then detailed in

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Section 3. Section 4 presents extensive computational results obtained from solving a set of randomly generated test problems and demonstrate the efficiency of the proposed hybrid algorithm. Finally, Section 5 concludes this research.

II. Problem Statement and model formulation

A. Problem Statement

Fig.1 describes the supply chain network under consideration.

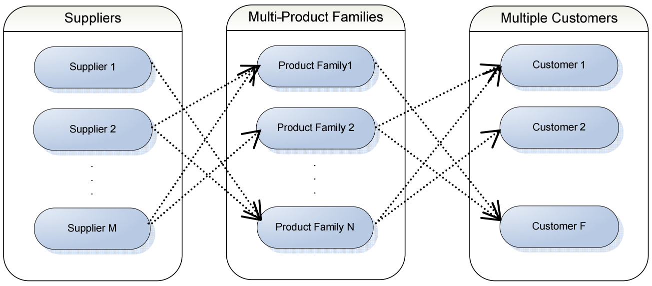

Fig.1 Supply chain network

As shown in Fig.1, a manufacturer aims to meet different needs of customers by producing multiple families of products, with multiple product variants in each family. These product families share common and non-common modules, such as raw materials and parts. With limited capacity of suppliers, it is important to determine the supply quota among different supplier groups for manufacturing multiple products. The problem is further complicated by the multiple selection criteria for selecting suppliers such as: price, quality, on-time delivery and trust [3]. The objective of this paper is therefore to:

1) Determine the production quantity of each product variant
2) Select the most suitable suppliers based on the selection criteria and their capacity and split the orders among these suppliers
3) Maximize the manufacturer's profit

B. Model Formulation

This section presents the development of a new mixed integer programming mathematical model describing the characteristics of the research problem. A manufacturer aims to produce n families of products to satisfy the customer demands in a multiple period planning horizon. Each product family has I^n product variants (for example: different colors, sizes etc.) to cater for different customer requirements, and utilizes L "AND modules" and K "OR modules" provided by m capacity-constrained suppliers. To characterize the product structure, a genetic-bill-of-material (GBOM) method (see [5]) is adopted.

To facilitate the presentation, the notations are firstly listed as follows.

Indices:

k	OR module
S_k	number of options for OR module k
ks	option s of module k
l	AND module
n	product family
I^n	number of product variants in family n
ni	product variant i of family n
m	supplier
τ	time period
T	number of all time periods

Parameters:

z_{niks}	1 if ks is used for product ni, 0 otherwise
z'_{nl}	1 if l is used for product ni,0 otherwise
V^{τ}_{mks}	capacity of supplier m for ks in period τ
G^{τ}_{ml}	capacity of supplier m for l in period τ
ω^{τ}_{mks}	supplier m's selling price for ks in period τ
b^{τ}_{ml}	Supplier m's selling price for l in period τ
$Q^{n\tau}$	market demand for family n in period τ
BOM_{nk}	units of k needed to produce one unit of final product variant in family n
BOM'_{nl}	units of l needed to produce one unit of final product variant in family n
F_{ni}	fixed cost for marking down the less desirable product ni
C_{ni}	production cost for one unit of product ni
S_{ni}	setup cost for one unit of product variant ni
B^{τ}_{m}	supplier m's minimum budget in period τ
T^{τ}_{m}	supplier m's trust level in period τ
O^{τ}_{m}	transaction cost of supplier m in period τ
p^{τ}_{n1}	retail price for the ideal variant of family n in period τ
p^{τ}_{ni}	retail price for the product ni in period τ
H_{ks}	inventory holding cost for ks
H'_{l}	inventory holding cost for l
HH_{ni}	inventory holding cost for product ni
d^{τ}_{m}	late delivery days of m in period τ
TP_{ni}	unit tardiness penalty for product ni per day
QP	quality penalty for one unit of the modules per percent below 100%
QL^{τ}_{mks}	quality level of ks procured from m in period τ
QL'^{τ}_{ml}	quality level of l procured from m in period τ
δ^{τ}_{mks}	1if m is capable of providing ks in period τ, 0 otherwise
δ'^{τ}_{ml}	1if m is capable of providing l in period τ, 0 otherwise

Continuous variables:

Q^{τ}_{ni}	quantity of product ni produced in period τ
A^{τ}_{ni}	quantity of product ni sold in period τ

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x_{mks}^{τ}	order quantity of ks from m in period τ
$x_{ml}^{'\tau}$	order quantity of l from m in period τ
I_{ks}^{τ}	inventory level of ks in period τ
$I_{l}^{'\tau}$	inventory level of l in period τ
II_{ni}^{τ}	inventory level of product ni in period τ

Binary variables:

y_{mks}^{τ}	1 if ks is procured from supplier m in period τ, 0 otherwise
$y_{ml}^{'\tau}$	1 if l is procured from supplier m in period τ, 0 otherwise
Y_{m}^{τ}	1 if supplier m is selected in period τ, 0 otherwise
η_{ni}^{τ}	1 if product ni is produced in period τ, 0 otherwise
ζ_{ni}^{τ}	1 if product ni is sold in period τ, 0 otherwise

Mathematical model:

Objective:

Maximize: Total profit = Total revenue - Total costs

Total Revenue = $\sum_{\tau=1}^{T}\sum_{n=1}^{N}\sum_{i=1}^{I^n} A_{ni}^{\tau}\zeta_{ni}^{\tau}p_{ni}^{\tau}$

Total costs= $\sum_{c=1}^{9}$ Costc

Cost1:

Total purchasing cost of modules=

$$\sum_{\tau=1}^{\mathrm{T}}\sum_{m=1}^{M}\sum_{k=1}^{K}\sum_{s=1}^{S_k} x_{mks}^{\tau}\omega_{mks}^{\tau}+\sum_{\tau=1}^{\mathrm{T}}\sum_{m=1}^{M}\sum_{l=1}^{L} x_{ml}^{\tau}b_{ml}^{\tau}$$

Cost2:

Total transaction cost with both the module suppliers =

$$\sum_{\tau=1}^{\mathrm{T}}\sum_{m=1}^{M} O_{m}^{\tau}Y_{m}^{\tau}$$

Cost3:

Cost incurred by the efforts in promotion, advertising, to lure the customer to buy the products = $\sum_{\tau=1}^{\mathrm{T}}\sum_{n=1}^{N}\sum_{i=1}^{I^n} Q_{ni}^{\tau}\eta_{ni}^{\tau}F_{ni}$

Cost4:

Total quality penalty= $$QP\times\sum_{\tau=1}^{\mathrm{T}}\sum_{m=1}^{M}\sum_{k=1}^{K}\sum_{s=1}^{S_k}(1-QL_{mks}^{\tau})x_{mks}^{\tau} +QP\times\sum_{\tau=1}^{T}\sum_{m=1}^{M}\sum_{l=1}^{L}(1-QL_{ml}^{\tau})x_{ml}^{\tau}$$

Cost5:

Total tardiness penalty= $\sum_{\tau=1}^{\mathrm{T}}\sum_{n=1}^{N}\sum_{i=1}^{I^n}\zeta_{ni}^{\tau}\times TP_{ni}\times PD$,

where

$$PD=\max\left\{\arg\max_{d_m^{\tau}}\left(z_{niks}\times y_{mks}^{\tau}\times d_{m}^{\tau}\right),\arg\max_{d_m^{\tau}}\left(z_{nl}^{'}\times y_{ml}^{\tau}\times d_{m}^{\tau}\right)\right\}$$

Cost6:

Total inventory holding cost for the modules =

$$\sum_{\tau=1}^{\mathrm{T}}\sum_{k=1}^{K}\sum_{s=1}^{S_k} I_{ks}^{\tau}H_{ks}+\sum_{\tau=1}^{T}\sum_{l=1}^{L} I_{l}^{'\tau}H_{l}^{'}$$

Cost7:

Total inventory holding cost for the final products=

$$\sum_{\tau=1}^{\mathrm{T}}\sum_{n=1}^{N}\sum_{i=1}^{I^n} II_{ni}^{\tau}HH_{ni}$$

Cost 8:

Total production cost = $\sum_{\tau=1}^{T}\sum_{n=1}^{N}\sum_{i=1}^{I^n} Q_{ni}^{\tau}\eta_{ni}^{\tau}C_{ni}$

Cost 9:

Total production setup cost= $\sum_{\tau=1}^{T}\sum_{n=1}^{N}\sum_{i=1}^{I^n}\eta_{ni}^{\tau}S_{ni}$

Subject to:

$$0\le x_{mks}^{\tau}\le V_{mks}^{\tau},\quad \forall m,k,s,\tau \tag{1}$$

$$0\le x_{ml}^{t}\le G_{ml}^{t},\quad \forall m,l,t \tag{2}$$

$$\sum_{k=1}^{K}\sum_{s=1}^{S_k} x_{mks}^{\tau}\omega_{mks}^{\tau}+\sum_{l=1}^{L} x_{ml}^{\tau}b_{ml}^{\tau}>B_{m}^{\tau},\forall m,k,s,l,\tau \tag{3}$$

$$I_{ks}^{\tau-1}+\sum_{m=1}^{M} x_{mks}^{\tau}\ge\sum_{n=1}^{N}\sum_{i=1}^{I^n} z_{niks}\eta_{ni}^{\tau}Q_{ni}^{\tau}BOM_{nk},\quad \forall m,k,s,n,i,\tau,\tau\ne \mathrm{T} \tag{4}$$

$$I_{ks}^{\mathrm{T}-1}+\sum_{m=1}^{M} x_{mks}^{\mathrm{T}}=\sum_{n=1}^{N}\sum_{i=1}^{I^n} z_{niks}\eta_{ni}^{\mathrm{T}}Q_{ni}^{\mathrm{T}}BOM_{nk},\forall m,k,s,n,i \tag{5}$$

$$I_{l}^{'(\tau-1)}+\sum_{m=1}^{M} x_{ml}^{'\tau}\ge\sum_{n=1}^{N}\sum_{i=1}^{I^n} z_{nl}^{'}\eta_{ni}^{\tau}Q_{ni}^{\tau}BOM_{nl}^{'},\quad \forall m,l,n,i,\tau,\tau\ne \mathrm{T} \tag{6}$$

$$I_{l}^{'(\mathrm{T}-1)}+\sum_{m=1}^{M} x_{ml}^{'\mathrm{T}}=\sum_{n=1}^{N}\sum_{i=1}^{I^n} z_{nl}^{'}\eta_{ni}^{\mathrm{T}}Q_{ni}^{\mathrm{T}}BOM_{nl}^{'},\forall m,l,n,i \tag{7}$$

$$\sum_{i=1}^{I^n}\zeta_{ni}^{\tau}A_{ni}^{\tau}=Q^{n\tau},\forall n,i,\tau \tag{8}$$

$$Q_{ni}^{\tau}+II_{ni}^{\tau-1}\ge A_{ni}^{\tau},\forall n,i,\tau \tag{9}$$

$$\sum_{\tau=1}^{T}\sum_{i=1}^{I^n}\eta_{ni}^{\tau}Q_{ni}^{\tau}=\sum_{\tau=1}^{T}\sum_{i=1}^{I^n}\zeta_{ni}^{\tau}A_{ni}^{\tau}=\sum_{\tau=1}^{T}Q^{n\tau},\forall n,i,\tau \tag{10}$$

$$II_{ni}^{\tau}=II_{ni}^{\tau-1}+Q_{ni}^{\tau}-A_{ni}^{\tau},\forall n,i,\tau \tag{11}$$

$$II_{ni}^{0}=0, II_{ni}^{T}=0,\forall n,\forall i \tag{12}$$

$$p_{ni}^{\tau}=p_{n1}^{\tau}\sqrt[\alpha]{(u_{ni})^{\beta}} \tag{13}$$

$$y_{mks}^{\tau}=\min(1,x_{mks}^{\tau}),\forall m,k,s,\tau \tag{14}$$

$$y_{ml}^{'\tau}=\min(1,x_{ml}^{'\tau}),\forall m,l,\tau \tag{15}$$

$$Y_{m}^{\tau}=\min(1,y_{mks}^{\tau}+y_{ml}^{'\tau}),\forall m,k,s,l,\tau \tag{16}$$

$$\eta_{ni}^{\tau}=\min(1,Q_{ni}^{\tau}),\forall n,i,\tau \tag{17}$$

$$\zeta_{ni}^{\tau}=\min(1,A_{ni}^{\tau}),\forall n,i,\tau \tag{18}$$

$$0\le x_{mks}^{\tau}\le\delta_{mks}^{\tau}\times M_{\infty},\forall m,k,s,\tau \tag{19}$$

$$0\le x_{ml}^{'\tau}\le\delta_{ml}^{'\tau}\times M_{\infty},\forall m,l,\tau \tag{20}$$

The objective function is to maximize the manufacturer's total profit. Constraints (1) and (2) indicate that the suppliers have limited capacity for the OR and AND modules. Constraint (3) represents the lowest purchasing amount required by the suppliers. Constraints (4)-(7) imply the relationship between available resources and the production quantity of the final products over the planning horizon, i.e., BOM constraints. The demand satisfaction requirement and the relationship between the production and sale quantity of the final products are governed by constraints (8)-(10).

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Constraints (11) and (12) ensure that the inventory balances the final products. Price discounts for the less desirable product variants with customer flexibility considerations are given in equation (13), where p^t_{n1} is the retail price for the ideal product variant, α and β refer to price elasticity and utility elasticity, respectively. Constraints (14)-(18) govern that $y^t_{mks}, y^t_{ml}, Y^t_m, \eta^t_{ni}, \zeta^t_{ni}$ are 0,1 integer variables. Constraints (19) and (20) govern the procurement of modules from suppliers, where M_∞ is a large positive number.

C. An Illustrative Example

A simple numerical example is presented to illustrate how the proposed integrated supplier selection and order allocation problem can be formulated and applied in a multi-product supply chain.

Consider a manufacturer who aims to produce two families of products to meet different customer needs. The customers have specifications regarding the shape, color and material used for the products.

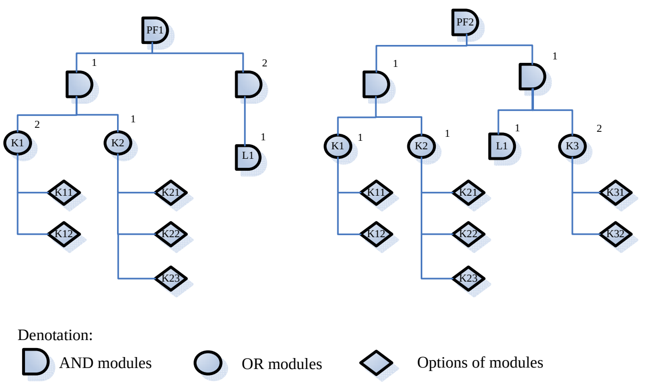

Fig.2 GBOM for Two Product Families

As shown in Fig.2, a three-level GBOM is used to depict the product structure of the product families. The maximum number of the OR modules in the lowest level is set to 3, as indexed by $K1, K2, K3$. These modules embody the shape, color and material requirements of the specific modules, respectively. There is only one AND module ($L1$) in the lowest level. The details of the three OR modules are given as below.

Module $K1$	Module $K2$	Module $K3$
$K11$: rectangular	$K21$: green	$K31$: plastics
$K12$: circular	$K22$: yellow	$K32$: steel
	$K23$: white	

Hence, the total numbers of variants in each product families can be calculated as 2×3, $2\times3\times2$, respectively. Using the proposed hybrid algorithm, the solutions to this example can be obtained as follows.

Production quantities of product variants:

In product family 1, only two variants are produced, i.e., $Q^1_{11} = 85, Q^1_{14} = 48$,

The product variants produced in family 2 are: $Q^1_{22} = 40, Q^1_{25} = 57$.

The production quantities of all the other variants are zero.

Order quantity of OR and AND modules:

	Supplier 1	Supplier 2	Supplier 3
K11	267	0	0
K12	0	96	0
K21	73	100	0
K22	0	0	0
K23	0	0	57
K31	0	54	50
K32	0	0	80
L1	200	0	63

III. HYBRID ALGORITHM

The problem described by the proposed mixed integer programming model is NP-hard, which needs to be solved by an efficient computational method. Hence, this section focuses on the development of a new hybrid algorithm based on the strengths of both constraint programming and simulated annealing.

A. Notations

The following notations are firstly listed to facilitate the presentation of the algorithm.

t	temperature iteration index ($t = 0,1,..., max\_t$)
N_d	set of indices for all the product variants
d	index for the product variants, $d \in N_d$
N_e	Ne is the set of indices for all the feasible solutions in an iteration. *Ne* is also the Markov chain length of simulated annealing
e	index for a complete feasible solution, $e \in N_e$
E_Best	optimal solution among all the feasible sequences within an iteration (local optimum)
T_Best	optimal solution among all the iterations (global optimum)

B. Basic Steps of the Hybrid CP-SA

The basic procedures of the hybrid CP-SA algorithm are then outlined as follows.

Step 1: Set t =0, set the initial temperature of simulated annealing as $Tem_0 = \dfrac{\text{Cost}_{\min} - \text{Cost}_{\max}}{\ln Pac_0}$, here $\text{Cost}_{\min}$ and $\text{Cost}_{\max}$ are the minimum and maximum bounds of problem complexity, the initial acceptance probability Pac_0 is set very close to 1. The resulting high initial temperature provides a high degree of randomness and most of the movements are accepted in the initial stage. Set $e = 0$.

Step 2: Select an input node d (product variant) for constraint programming based on the retail price, i.e., $d^* = \arg\max_{d \in N_d} (\text{Price}_d)$, set $d^* = 1$. Generate the value of Q_1^t within the feasible range bounded by demand, capacity of raw materials.

Step 3: Search for a complete feasible solution
a) if $d < |N_d|$, then let $d = d + 1$, use constraint programming algorithm to generate the value for Q_d^t, reduce the search space.
b) else if $d = |N_d|$, then one complete feasible solution $q_e^t = \{Q_1^t, Q_2^t, ..., Q_{N_d}^t\}$ has been found. Initialize this solution as the current optimal solution. $E\_Best = q_e^t$, $e = e + 1$.

Step 4:
Generate a neighborhood solution starts from $d = d + 1$ using the constraint programming algorithm.

Step 5: Compare the two solutions using the proposed SA algorithm.
a) if the neighborhood solution replaces the current optimal solution, i.e., $\dfrac{\exp(-Fitness(q_e^t) - Fitness(E\_Best))}{Tem_t} > \rho$, where ρ is a real number randomly generated between 0 and 1, then $d = d + 1$,generate another neighborhood solution starting from d using constraint programming approach, $e = e + 1$;
b) else if the neighborhood solution doesn't replace the current optimal solution,
then $d = d - 1$, generate another neighborhood solution starting from d using constraint programming approach, $e = e + 1$.

Step 6: If $e < |N_e|$, then repeat Step 5 until $e = |N_e|$, then let $t = t + 1$, update T_Best, then go to step 7.

Step 7: Calculate the temperature of the new iteration, i.e., $Tem_t = \alpha Tem_{t-1}$, set $e = 0$. Here α is the cooling rate of the proposed simulated annealing algorithm, which belongs to (0,1). The cooling rate α is dependent on the variance ($Var_{Tem_{t-1}}$) of the objective function values provided by the feasible solutions at the temperature Tem_{t-1}. The mean value and variance ($Var_{Tem_{t-1}}$) of the objective function values is calculated as follows:

$$Mean_{Tem_{t-1}} = \frac{1}{|Ne|} \sum_{\forall e \in Ne} Fitness(q_e^t)$$

$$Var_{Tem_{t-1}} = \frac{1}{|Ne|} \sum_{\forall e \in Ne} (Fitness(q_e^t) - Mean_{Tem_{t-1}})^2$$

The definition of [8] for cooling rate α is then applied:

$$\alpha = \frac{1}{1 + \left(\ln(1+\delta) Tem_{t-1} / 3Var_{Tem_{t-1}}\right)}$$

where δ is a control rate and experimentally determined as 0.01. Repeat steps 2-5 until $e = |N_e|$.

IV. Test Problems and Computation Results

A. Test Problems

The effectiveness of the proposed hybrid CP-SA algorithm is demonstrated by solving a set of randomly generated test problems and by comparing the results obtained with those obtained by using ILOG OPL.

In the integrated supplier selection and order allocation problem for multi-product manufacturing, the number of product families considered ranges from 4 to 8. Each product family has a unique product structure depicted in its GBOM. The number of suppliers are randomly generated within the ranges [2,6]. The number of time periods is randomly generated within the range [1,6]. 20 test problems are used in the experiments.

The algorithm is programmed in C++ and run on a Pentium IV 3.2 GHz computer with 512M Ram.

B. Computation Results and Discussions

Figure 3 shows the convergence behavior of the proposed hybrid CP-SA algorithm when the iteration number ranges from 10 to 100 and the values for Pac_0 and N_e are determined as 0.99 and 60, respectively.

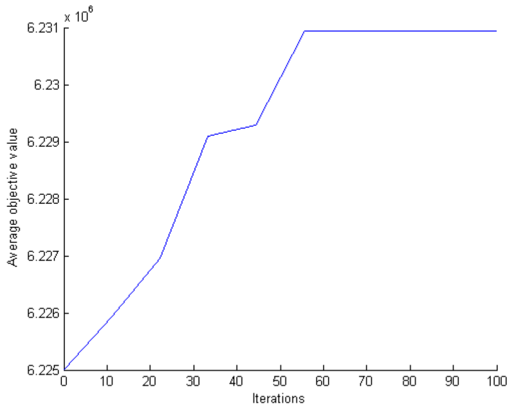

Fig 3. Average objective values in different iterations

Table 1 summarizes the best and the average of the best solutions obtained by running the proposed hybrid algorithm 5 times. The average computation times needed to achieve the best solutions are also included.

The results in the table 1 show that, the proposed hybrid CP-SA algorithm can locate near-optimal solution obtained by ILOG OPL with less computation cost. For small and middle scale problems, the differences are within 0.8% and 1.5% as compared to the optimal solutions obtained by ILOG OPL, respectively. For large scale cases, the hybrid algorithm can find better solutions (bold numbers) with less computational cost. The "---"indicates there is no solution found after running ILOG for the times listed in the table.

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Table 1 Computation Results

No	CP-SA			ILOG	
	avg	best	time	solution	time
1	6230942	6253590	0.16s	6297116	0.38s
2	865834	878028	0.27s	878439	0.48s
3	811032	816235	0.35s	821093	0.52s
4	1089033	1089037	0.45s	1089733	0.82s
5	544283	544611	0.66s	545163	1.04s
6	1198525	1204146	0.75s	1216688	1.61s
7	1403233	1409490	0.95s	1433080	1.82s
8	1422288	1426626	0.92s	1481515	2.58s
9	592299	592369	1.10s	597152	2.88s
10	2369706	2557677	1.25s	2557999	3.09s
11	1352883	1353818	1.33s	1380407	3.72s
12	17278360	17301138	5.35s	17467460	13.9s
13	1352883	1380142	6.35s	1389411	17.3s
14	1710104	1714143	8.00s	1738481	24.3s
15	1531070	1542378	20.3s	1558840	44.5s
16	1779720	**1808741**	15.5s	---	160s
17	2165533	**2184312**	16.2s	---	200s
18	1556391	**1558840**	30.0s	---	300s
19	934288	**937744**	35.0s	---	360s
20	1271565	**1284232**	60.0s	---	400s

V. Conclusions

In this paper, a novel mixed integer programming model has been formulated for solving the integrated supplier selection and order allocation problem that occurs in the design of a multi-product supply chain operating under a multi-period manufacturing scenario. A new hybrid CP-SA algorithm has also been developed by combining the strengths of both constraint programming and simulated annealing for solving this complex problem. In the hybrid algorithm, CP has been used to generate the initial feasible solution and SA has been used to guide the search path. Unlike traditional SA, CP has been used to generate the neighborhood solutions for SA. Useful information obtained from CP helps to reduce the search space. The proposed algorithm has been tested with a set of randomly generated test problems. Indeed, the proposed methodology has been shown to be efficient and effective for making optimal decisions on supplier selection and order allocation.

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References

[1] Azizi, N., Zolfaghari, S., Adaptive temperature control for simulated annealing: a comparative study, *Computers & Operations Research*, 31, pp. 2439–2451, 2004.
[2] Bartak, R., "Theory and Practice of Constraint Propagation", in *Proceedings of the 3rd Workshop on Constraint Programming for Decision and Control (CPDC2001)*, Wydavnictvo Pracovni Komputerowej, Gliwice, Poland, pp. 7-14, June 2001.
[3] C. Weber, J. Current, and W.Benton, "Vendor selection criteria and methods", *European Journal of Operational Research*, Vol. 50, pp.2-18, 1991.
[4] C. Weber and J. Current, "A multi-objective approach to vendor selection", *European Journal of Operational Research*, Vol. 68, pp.173-184, 1993.
[5] J. Jiao, "Generic bill-of-materials-and-operations for high variety production management", *Concurrent Engineering: Research and Application*, Vol.8, No.4, pp.297-322, 2000.
[6] Kirkpatrick, S., Gelatt Jr., C.D., Vecchi, M.P., Optimization by simulated annealing. *Science* 1983, 220, pp. 671–680.
[7] L. Jacques, "An optimization model for selecting a product family and designing its supply chain", *European Journal of Operational Research*, Vol. 169, pp.1030-1047, 2006.
[8] Tavakkoli-Moghaddam, R., Aryanezhad, M.B., Safaei, N., Azaron, A., Solving a dynamic cell formation problem using metaheuristics, Applied Mathematics and Computation, 170, pp.761-780，2005.
[9] Tsang, E. *Foundations of Constraint Satisfaction*, Academic Press, London, 1995.