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Optimization of Consignment Stock Policy Using Particle Swarm Algorithm

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Abstract: *In recent years, companies have strengthened their supply agreements, and even the management of their inventories. To this aim, a particular VMI policy, known as Consignment Stock (CS) represents an interesting strategy to stock monitoring and control for both the buyer and the supplier, and it has been progressively considered and introduced in several companies. CS has been previously analyzed for single vendor single buyer case (1986). In this project, we have analyzed analytical model for single vendor multi buyer CS policy. Four types of models, basic CS model, CS with delay, CS with delay with information sharing; CS with crashing lead time. The main objective of this work is to optimize the Joint Total Economic cost of each model. Analytical model is solved with enumeration technique up to five buyers. For more than five buyers, solving analytical model with complete enumeration becomes computationally expensive. To overcome this problem Particle Swarm Algorithm (PSO) is proposed for finding optimum for the case of more than five buyers. PSO model is developed and can solve more than ten buyers. So Particle Swarm Algorithm (PSO) is used for the optimization of the above four models. A generalized C program has been written to implement the above problem using Particle Swarm Algorithm (PSO).*
Keywords: *Numerical approach, Total cost, Taguchi,*

I. Introduction

1.1 Consignment stock policy strategies:

The consignment stock policy was developed for three different models in the case of single vendor – single buyer and single vendor –multi buyer. For single vendor –single buyer: basic consignment stock policy, consignment stock policy with delay deliveries, and consignment stock policy with controllable lead times. For single vendor –multi buyer: Basic consignment stock policy, Consignment stock policy with delay deliveries, Consignment stock policy with information sharing with delay deliveries, consignment stock policy with controllable lead times.

1. CSP model:
This is a basic model in which basic concepts and a condition of the consignment stock has been implemented.

2. CSP model with delay deliveries: The basic CSP model may not be suitable for the limited periods because the maximum level of the buyer’s inventory may reach immediately. Therefore consignment stock policy with delayed delivery is an alternate policy. In this model, the last delivery is delayed until it reaches that there is no further increase in the maximum level already reached. That means it has to delay the stock always whenever maximum level inventory stock at the buyer is reached. Hence it doesn’t allow exceeding the maximum limit ‘S’ in the buyer’s inventory. In this situation the shipments if any with vendor has to wait at vendor’s place.

3. CSP with delay with information sharing:
In the previous model we have not considered the effect of information sharing on the inventory. There are four common types of information sharing strategies for a supply chain of a single product:
(1) Order information sharing where every stage of the supply chain only knows the orders from its immediate downstream stage;
(2) demand information sharing where every stage of the supply chain has full information about consumer demand;
(3) Inventory information sharing where each stage shares its inventory and demand information with its immediate upstream stage; and
(4) Shipment information sharing where every stage shares its shipment data with its immediate upstream stage
Order information sharing is common between two parties. Inventory and shipment information sharing will lead to reduction in the inventory cost. Due to information sharing vendor will know inventory status of the buyer all the time. Vendor can thus decide which buyer can accommodate the delayed delivery and the delayed delivery from one buyer is transferred to that buyer. Here principle assumption made to simplify the problem is

that the shifted quantity to another buyer will be same as his economic order quantity and vendor will make necessary changes in the shipment size.

4. CSP with controllable lead time:

In recent years industries have devoted considerable attention in reducing the inventory cost. The characteristics of JIT systems are consistent high quality, small lot sizes, frequent delivery, short lead time and close supplier ties. Hence the control of lead time is one of the key factors to the success of JIT production. Traditionally the lead time of an inventory model is hypothesized as known (Kim and Park, 1985) or with certain probability distribution (Foot et al.1988). Actually, lead time can be reduced by an additional crashing cost, so as to improve customer service level, and reduce inventory in safety stocks i.e., it is controllable. When the assumption of deterministic consumer demand is assumed to be stochastic, lead time becomes an important issue and its control leads to many benefits. The Japanese experience of using JIT production shows that there are advantages and benefits associated with their efforts to control lead time. In many practical situations lead time can be reduced at an added cost. Lead time is reduced one at a time starting from the first independent component because it is having minimum unit crashing cost per unit time, and the second independent component and so on. It is clear that when lead time is reduced, its corresponding handling cost for that time is to be reduced, but the crashing cost is added to the total cost of the buyer. Since lead time is a decision variable in this model, the extra costs incurred by the vendor will be fully transferred to the buyer if shortened lead time is requested.

1.2 Limitations of analytical model:

All four models are developed for two, three and four buyers. Solving analytical model becomes computationally more expensive as the number of buyers increases. For one vendor three buyers CS with delay with information sharing, its taking more than 1 hour to calculate the optimum whereas for one vendor four buyers CS with delay with IS, results could not be obtained even after 48 hours. Therefore solving analytical model by complete enumeration is almost impossible for more than five buyers. One of the solutions to above problem is to develop a heuristic algorithm to solve the model. We propose a Particle Swarm Algorithm to find optimum values of variables that will give minimum joint total cost.

II. Generalizing The Basic Cs Model For Multiple Buyers

2.1 For basic CS model:

$\mathbf{T_c} = \frac{s+\sum_{i=1}^{y} A_i + \sum_{i=1}^{y} n_i \cdot At_i}{c} + h_v \frac{c}{2p}[\sum_{i=1}^{y} \frac{D_i^2}{n_i}] + \sum_{i=1}^{y} \left(\frac{h_{bi}}{2}\left\{D_i c - (n_i - 1)D_i \left[\frac{D_i c}{n_i p} + \sum_{i\neq j} \frac{D_i c}{n_j p}\left(\frac{n_i}{n_j}\right)\right]\right\}\right) + \sum_{i=1}^{y}\left(hb_i \cdot z \cdot \sigma_i \cdot\right.$ Li +i=1yπi· σi ·Li · φzc------- (1)

2.2 CS with Delay Model For Multiple Buyers:

$\mathbf{T_c} = \frac{s+\sum_{i=1}^{y} A_i + \sum_{i=1}^{y} n_i \cdot At_i}{c} + h_v c\left\{\frac{1}{2p}\left[\sum_{i=1}^{y} \frac{D_i^2}{n_i}\right] + \sum_{i=1}^{y}\left(\frac{D_i}{n_i}\frac{(p-D_i)}{n_i p}\frac{(k_i+1)}{2}k_i\right)\right\} + \sum_{i=1}^{y}\left\{\frac{hb_i}{2}\left\{(n_i - k_i)\frac{D_i c}{n_i} - \right.\right.$

ni−ki−1DiDicnip+i≠jDjcnjpnjni + i=1yhbi·z·σi·Li +i=1yπi· σi ·Li · φzc ---------- (2)

2.3 CS with Delay and Information Sharing:

$\mathbf{T_c} = \frac{s+\sum_{i=1}^{y} A_i + \sum_{i=1}^{y} n_i \cdot At_i}{c} + h_v c\left\{\frac{1}{2p}\left[\sum_{i=1}^{y} \frac{D_i^2}{n_i}\right] + \sum_{i=1}^{y}\left(\frac{D_i}{n_i}\frac{(p-D_i)}{n_i p}\frac{(k_i-m_i+1)}{2}(k_i - m_i)\right)\right\} + \sum_{i=1}^{y}\left\{\frac{hb_i}{2}\left\{\left(n_i - k_i + \right.\right.\right.$

j≠ijijDicni−ni−ki−1+j≠ijijDiDicnip+i≠jDjcnjpnjni + i=1yhbi·z·σi·Li +i=1yπi· σi ·Li · φzc-----(3)

2.4 Cs with Crashing Lead Time Model For Multiple Buyers:

$\mathbf{T_c} = \frac{s+\sum_{i=1}^{y} A_i + \sum_{i=1}^{y} n_i \cdot At_i}{c} + h_v \frac{c}{2p}[\sum_{i=1}^{y} \frac{D_i^2}{n_i}] + \sum_{i=1}^{y} \left(\frac{h_{bi}}{2}\left\{D_i c - (n_i - 1)D_i \left[\frac{D_i c}{n_i p} + \sum_{i\neq j} \frac{D_i c}{n_j p}\left(\frac{n_i}{n_j}\right)\right]\right\}\right) + \sum_{i=1}^{y}\left(hb_i \cdot z \cdot \sigma_i \cdot\right.$ Li +i=1yπi· σi ·Li · φzc + i=1yCLic-----(4)

III. Iterative Algorithm For The Proposed Pso Model

Step 1: Initialize the swarm , P(t), of particles such that the position $X_i(t)$ of each particle Pi belongs to P(t) is random within the hyperspace (starting with t = 0).
Step 2: Initialize a swarm of velocity V(t), such that the velocity $V_i(t)$ of each particle P_i belongs to V(t) is random within the hyperspace with t = 0 and follows the following function:

$$V_i(t) = \begin{cases} -4 & \text{if} \quad V_i(t) \le -4 \\ V_i(t) & \text{if} \quad -4 \le V_i(t) \le 4 \\ 4 & \text{if} \quad V_i(t) \ge 4 \end{cases}$$

Step 3: Now evaluate the performance of $F_i(t)$ for each particle $P_i(t)$, using its current position $X_i(t)$.

Step 4: Now the position $X_i(t)$ of particle $P_i(t)$ is set as Pbest i(t).
Step 5: Compare the performance of each individual to its best performance thus far:
If $F(X_i(t)) < F(X_i(t-1))$
Then set, $X_i(t) = Pbest_i(t)$ orelse $X_i(t-1) = pbest_i(t)$.
Step 6: Compare the performance of each particle with that of the best particle of the swarm.
If $F(X_i(t)) < F(gbest)$
Then set, $X_i(t) = gbest(t)$.
Step 7: Now change the velocity vector for each particle $P_i(t)$:

$$V_i(t+1) = W(t)*(V_i(t)) + c_1*r_1*(X_{ipbest}(t) - X_i(t)) + c_2*r_2*(X_{igbest} - X_i(t));$$

Where,
W = inertia weight.
c_1, c_2 = acceleration constants = 1 , 2 respectively
r_1, r_2 = positive constants = 0.2, 0.3 respectively.
Step 8: now update the positions of the particles, using their new velocities

$$X_i(t+1) = X_i(t) + V_i(t+1)$$

Now, t = t+1.
Step 9: Go to step 3 and repeat until the given number of iterations.
HERE,
$P(t) = [P_1, P_2, P_3, P_4, P_5, \ldots\ldots\ldots P_i\ldots];$
$P_i(t) = X_i(t);$
$X_i(t) = [X_{1i}, X_{2i}, X_{3i}, X_{4i}, \ldots\ldots X_{mi}\ldots];$
$V_i(t) = [V_{1i}, V_{2i}, V_{3i}, V_{4i}, \ldots\ldots\ldots V_{mi}..];$
X_{1i} implies **:** first dimension of ith particle
V_{1i} implies **:** velocity of first dimension of ith particle

IV. Results And Discussion

This study is focused around the implementation of an evolutionary particle swarm optimization technique on consignment stock policy models. This section carries the results and few discussions over the same. For the result, the input data (Table.1) is taken from HANS SIJADI et. Al.(2005). This input is for single vendor two buyers and three buyer problem but has now been extended to ten buyers

The input data is tabulated below:

Table 1: Input data

VENDOR				
PRODUCTION RATE/TOTAL DEMAND	HOLDNG COST PER UNIT(Rs)	SET UP COST(Rs)	SHORTAGE COST FOR BUYER(Rs)	INPUT DATA FROM HANS SIJADI .ET. AL (2005), EXTENDED TO TEN BUYERS
2.5	4	200	50	

BUYERS						
NO.OF BUYERS	DEMAND (UNITS PER YEAR)	STANDARD DEVIATION OF DEMAND	HOLDING COST PER UNIT(Rs)	TRANSPORTATION COST(Rs)	ORDERING COST(Rs)	Lead time(days)
1	10000	50	8	30	100	7
2	13000	60	8	30	100	7
3	8000	30	8	30	100	7
4	17000	60	5	30	100	7
5	6000	30	7	30	100	7
6	10000	50	8	30	100	7
7	8000	30	7	30	80	7

8	5000	30	7	30	80	7
9	10000	50	8	30	100	7
10	12000	50	7	20	80	7

Table 2: lead time components with crashing costs

S.NO.	LEAD TIME	CRASHING COST
1	7	0
2	5.25	0.7
3	3.5	2.8
4	2.62	7.2

.

Table 3: shows results of the above example by particle swarm approach. Optimum cycle time, optimum number of shipments for each buyer and optimum shipment size has also been calculated and tabulated as well. The maximum inventory that a buyer can have has also been listed in Table 3.

Table 3: result of the given example**.**

NO.OF BUYERS	TYPE OF MODEL	PSO RESULTS			
		OPTIMUM CYCLE TIME(YRS)	**OPTIMUM NO.OF SHIPMENTS**	**OPTIMUM SHIPMENT SIZE**	**MAX INVENTORY OF BUYER**
1V-2B	CS-BASIC	0.100	$n_1=9,n_2=3$	$q_1=112$ $q_2=433$	$b_{1MAX}=667$ $b_{2MAX}=981$
	CS-DELAY	0.106	$n_1=5,n_2=9$ $K_1=1,K_2=2$	$q_1=212$ $q_2=154$	$b_{1MAX}=615$ $b_{2MAX}=731$
	CS-IS	0.113	$n_1=10,n_2=10$ $K_1=7,K_2=4$ $M_1=3,M_2=1$ $J_{12}=1,j_{21}=1$	$q_1=113$ $q_2=147$	$b_{1MAX}=339$ $b_{2MAX}=700$
	CS-CLT	0.105	$n_1=4,n_2=3$	$q_1=263$ $q_2=455$	$b_{1MAX}=738$ $b_{2MAX}=1028$
1V-3B	CS-BASIC	0.107	$n_1=3,n_2=3$ $n_3=1$	$q_1=357$ $q_2=463$ $q_3=856$	$b_{1MAX}=807$ $b_{2MAX}=1047$ $b_{3MAX}=870$
	CS-DELAY	0.116	$n_1=10,n_2=9$ $n_3=1,K_1=2$ $K_2=1,K_3=1$	$q_1=116$ $q_2=168$ $q_3=928$	$b_{1MAX}=625$ $b_{2MAX}=890$ $b_{3MAX}=384$
	CS-IS	0.107	$n_1=10,n_2=9$ $n_3=9,K_1=7$ $K_2=6,K_3=4$ $M_1=5,M_2=5$ $M_3=4,j_{12}=3$ $j_{23}=1,j_{31}=1$	$q_1=107$ $q_2=155$ $q_3=106$	$b_{1MAX}=387$ $b_{2MAX}=740$ $b_{3MAX}=566$
	CS-CLT	0.107	$n_1=10,n_2=7$ $n_3=4$	$q_1=107$ $q_2=196$ $q_3=214$	$b_{1MAX}=711$ $b_{2MAX}=942$ $b_{3MAX}=613$
1V-4B	CS-BASIC	0.115	$n_1=7,n_2=2$ $n_3=3,n_4=2$	$q_1=165$ $q_2=747$ $q_3=307$ $q_4=977$	$b_{1MAX}=1133$ $b_{2MAX}=1223$ $b_{3MAX}=689$ $b_{4MAX}=1982$
	CS-DELAY	0.104	$n_1=10,n_2=10$ $n_3=8,n_4=7$ $K_1=5,K_2=1$ $K_3=2,K_4=1$	$q_1=104$ $q_2=136$ $q_3=104$ $q_4=253$	$b_{1MAX}=376$ $b_{2MAX}=811$ $b_{3MAX}=430$ $b_{4MAX}=1031$
	CS-IS	0.102	$n_1=9,n_2=8$ $n_3=7,n_4=8$ $K_1=8,K_2=7$ $K_3=6,K_4=7$ $M_1=7,M_2=6$ $M_3=5,M_4=4$ $j_{12}=6,j_{23}=5$ $J_{34}=4,j_{41}=2$	$q_1=115$ $q_2=166$ $q_3=117$ $q_4=217$	$b_{1MAX}=360$ $b_{2MAX}=745$ $b_{3MAX}=356$ $b_{4MAX}=967$
	CS-CLT	0.101	$n_1=8,n_2=7$ $n_3=6,n_4=4$	$q_1=127$ $q_2=188$ $q_3=135$ $q_4=430$	$b_{1MAX}=680$ $b_{2MAX}=890$ $b_{3MAX}=553$ $b_{4MAX}=1230$

Table 4 shows the various costs, included in the given PSO model. Total cost, incurred by vendor and the same incurred by individual buyer has also been tabulated in table5.4. The data shows that the cost, incurred by buyers in each model is less than that of their corresponding basic model. Percentage savings, obtained in different models with respect to basic model has also been enlisted below. It is very obvious, from the Table5.4 that the joint total economic cost of models (like: CS-delay, CS-information sharing, & CS-crash lead time) comes out to be less than that of their corresponding basic CS model.

Table 4: various costs, incurred by buyers and vendor in given model.

NO.OF BUYERS	TYPE OF MODEL	PSO RESULTS			
		COST, INCURRED BY VENDOR	COST, INCURRED BY BUYERS.	JTEC	% SAVING DUE TO PSO
1V-2B	CS-BASIC	2029	b_1=4956 b_2=4941	11926	NA
	CS-DELAY	2327	b_1=4752 b_2=3159	10238	14.1539
	CS-IS	2250	b_1=3625 b_2=4230	10110	15.2691
	CS-CLT	2240	b_1=3035 b_2=4180	9455	20.1044
1V-3B	CS-BASIC	2239	b_1=4933 b_2=4882 b_3=2558	14666	NA
	CS-DELAY	2789	b_1=3882 b_2=4669 b_3=2221	13561	14.3529
	CS-IS	2057	b_1=4894 b_2=4601 b_3=3165	12782	23.7556
	CS-CLT	2013	b_1=2550 b_2=3874 b_3=2614	11051	31.4673
1V-4B	CS-BASIC	2523	b_1=5647 b_2=5202 b_3=4733 b_4=3510	21615	NA
	CS-DELAY	2541	b_1=5258 b_2=4845 b_3=3433 b_4=3070	19148	11.4133
	CS-IS		NA	18500	14.3974
	CS-CLT	2116	b_1=4515 b_2=4187 b_3=3176 b_4=3087	17092	20.9252

4.1 A Comparative view of CPU time, consumed by particle swarm approach and analytical approach.
Table 5 shows a comparison between the computational time, elapsed in calculating, the results of different CS models, by analytical approach and by PSO approach. A pictorial comparison of the same can be viewed in Fig5.

Table 5: CPU time elapsed in analytical and PSO approach

NO.OF BUYERS	TYPE OF MODEL	ANALYTICAL APPROACH	PSO APPROACH	%SAVING OF CPU TIME IN PSO
		CPU TIME (s)	CPU TIME(s)	
1V-2B	CS-BASIC	0.09	0.77	-88.311
	CS -DELAY	1.89	0.85	122.35
	CS -IS	9.28	1.15	706.95
	CS -CLT	0.28	1.06	-73.58
1V-3B	CS-BASIC	0.73	1.64	-55.48
	CS-DELAY	NA	1.72	NA
	CS-IS	NA	1.89	NA
	CS-CLT	2.75	0.74	271.62
1V-4B	CS-BASIC	7.89	1.50	426.00
	CS-DELAY	NA	2.06	NA
	CS-IS	NA	2.07	NA
	CS-CLT	28.03	2.06	1260.67

4.2 Pictorial Representation of Foremost Results of Given PSO Model.

Few focal results, obtained after complete particle swarm enumeration of the given example have been pictorially sorted out in this section.

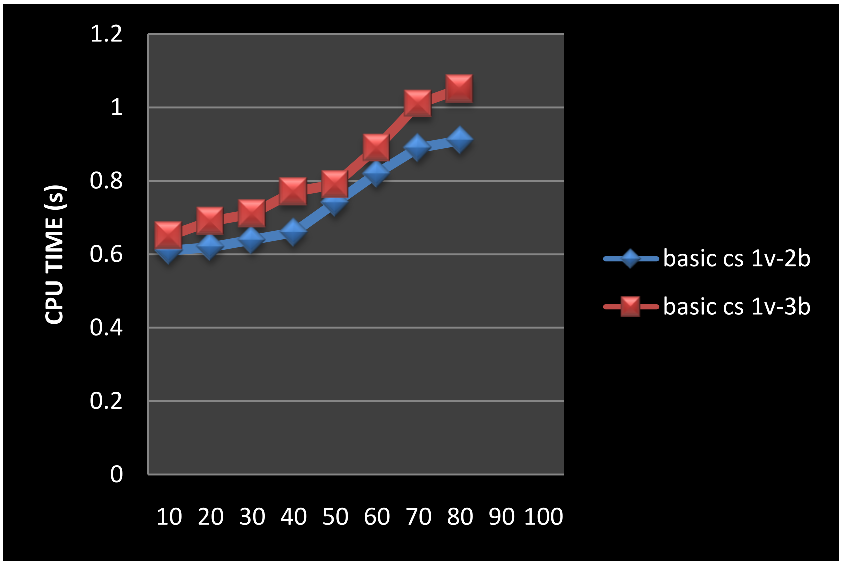

fig 1: no. of populations

CS model, it also indicates the working speed of algorithm with 1v-2b and 1v-3b basic CS models. Fig 1 shows the response of given algorithm with respect to basic CS 1v-2b and 1v-3b model. Fig 2 shows the variations in the joint total economic costs of different consignment stock policy models. Fig 3 shows the percentage savings of CS –delay, CS- with information sharing and CS-crashing lead time models over basic CS model.Fig5. Shows the percentage saving of CPU time in PSO over analytical approach.

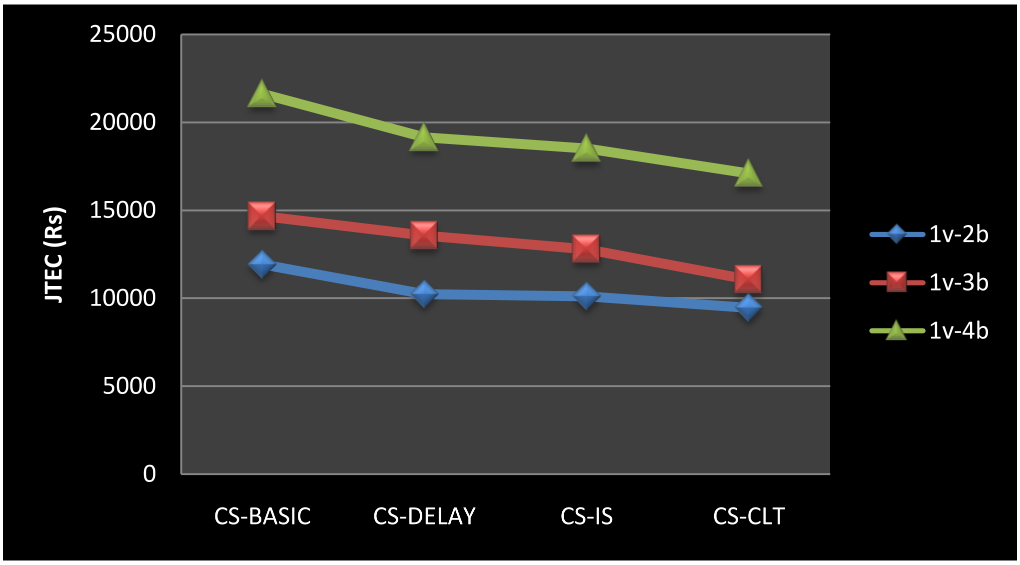

Fig 2: various models with their jtec.

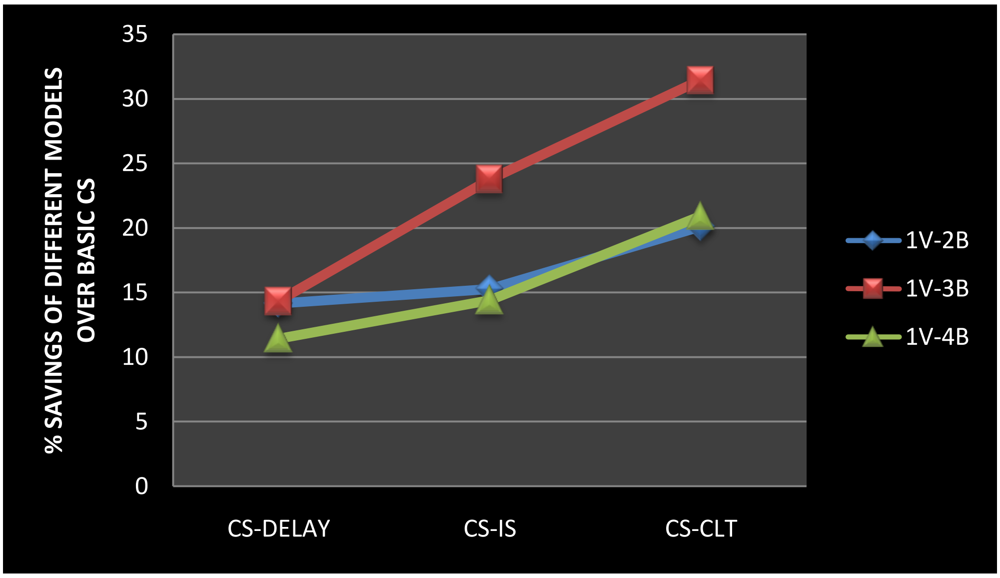

fig 3: percentage saving of diff.cs models with respect to basic cs model.

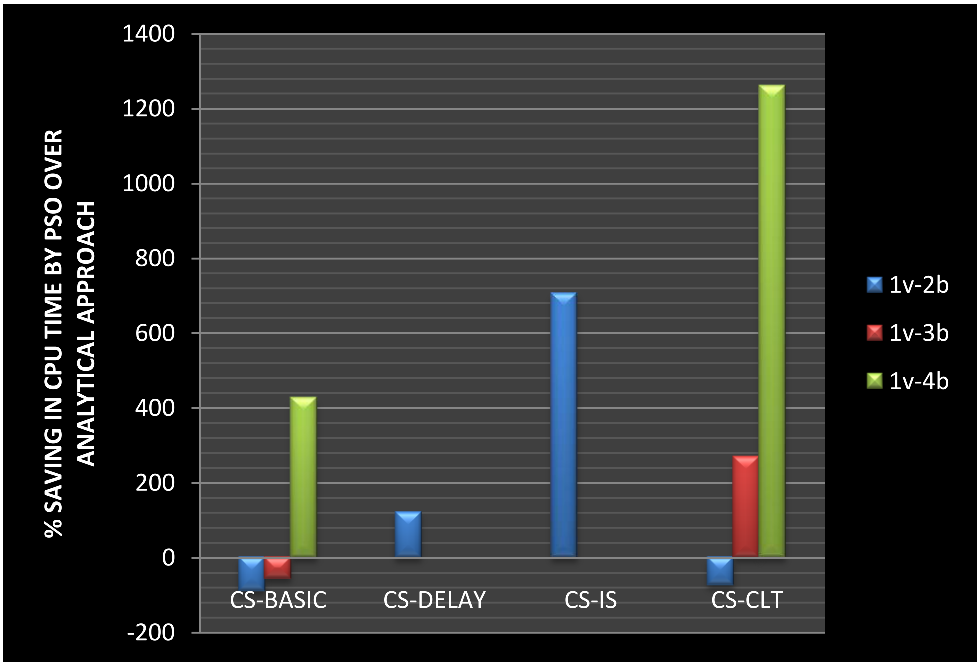

fig4: percentage saving in cpu time by pso over analytical approach.

V. Conclusion

1. An attempt is made to develop mathematical models for CSP in VMI and optimization of these models has been done by enumerative technique. Solving these mathematical models for many buyers is time consuming and may not be computationally economical.
2. The optimization of the same CS problem has been done by applying particle swarm optimization technique. The PSO models have been developed for CS problem and it has shown that the execution of PSO, leading to the optimal solutions, has taken a short span of time and thus, computationally better solutions have been obtained for number of buyers (currently upto four buyers).
3. JTEC for various buyers has been calculated and it took nearly 2 s for four buyer model against several hours of enumerative techniques.
4. The efficiency of the models has been tested thoroughly and it is found that solving the CS models for various buyers by using PSO is better, than, the same solved by enumerative techniques. Solving the JTEC for CS models by PSO is much better technique. A sensitivity analysis upto four buyer has also been done.

5. The results show that the CS-delay model, CS-IS model, CS-CLT model, all are incurring less JTEC than that of CS-basic model, irrespective of the buyer sizes. The percentage savings of each model with respect to CS-basic model has also been enlisted.

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