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UPDATED FOOD POSITIONS IN ARTIFICIAL BEE COLONY ALGORITHM FOR SUPPLY CHAIN MANAGEMENT

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Abstract

The present study deals with the management of supply chain using an updated Artificial Bee Colony (ABC) algorithm named UABC. UABC employs a linear combination of Gaussian and Cauchy distributions to update the candidate food positions from the older ones in memory. Optimization of a supply chain model is an integer programming problem or a constrained integer-mixed problem, for which suitable modifications are done in the algorithm. Statistical analysis of the proposed variant when compared with three ABC based algorithms indicates its efficiency and validity.

Key words: Artificial Bee Colony, ABC, supply chain system, optimization, exploration

1. INTRODUCTION

Supply chain management (SCM) and Supply chain models are gaining a lot of interest among researchers and business managers because of their practical utility. SCM is an integrated approach and can be defined as: "SCM is the coordination of production, inventory, location, and transportation among the participants in the supply chain to achieve the best mix of responsiveness and efficiency for the market being served" (Hugos, 2003).

Most of the supply chain models can be represented as optimization problems (linear or nonlinear in nature), with integer restrictions imposed on them and subject to various constraints (Mak & Wong, 1995). Due to the complexity of the mathematical models of SCM, application of classical techniques becomes quite difficult. Consequently, modern heuristic optimization techniques, such as simulated annealing and evolutionary algorithms, are getting much attention from the researchers (Zhou et al., 2002; Jeong et al., 2002; Syarif et al., 2002; Smirnov et al., 2004; Berning et al., 2004).

In the present study we have considered an example of SCM in pulp and paper industries. We have tried to minimize the sum of the inventory cost, manufacturing cost, transportation cost of the system related to pulp and paper industry Optimization technique employed is UABC, a modified variant of ABC (Karaboga, 2005; Karaboga & Basturk, 2007). Here we would like to mention that a preliminary version of UABC has been used to solve unconstrained problems and published in IEEE CEC 2012 proceedings (Sharma et al., 2012).

This paper is structured as follows: Section 2 describes supply chain in paper making and mathematical model of supply chain in pulp and paper. UABC is presented in section 4. Experimental settings and results are given in section 5. Finally, in section 6, the future scope and conclusion are presented.

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2. SUPPLY CHAIN IN PAPER MAKING

Paper manufacturing units are large scale process industries consisting of several integrated processes. These are *round the clock* industries consisting of a number of processes including procurement of raw material, its transportation, pulp and paper production, storage and finally the distribution of finished products to the merchants/customers. The management of these processes may be termed as the paper industry SCM (PISCM).

2.1. Components of Supply Chain

The first component of a PISCM, is the cost associated with the storage of raw material (consisting of soft and hard wood). It is possible to store harvested timber within a forest district before it is transported to the production mills. The second component is the cost associated with the transportation of the raw material to saw mills (the byproduct from saw mills in the form of wood chips is an important raw material used in pulp production) where the raw material is cut into logs. These logs are transported to the pulp mills by trucks, where the processing takes place for converting the raw material to pulp. The manufactured pulp and raw materials are stockpiled in local storage areas close to each mill. The limited size of these areas makes it important to find good schedules that keep storage levels as even as possible during production. The products are then distributed to the customers/buyers etc. The design of optimal production, inventory, and distribution system in the Pulp and Paper industry has been considered by a number of researchers (Stäblein et al., 2007; Christian et al., 2009; David et al., 2003).

The pictorial supply chain process in pulp and paper is presented in figure 1.

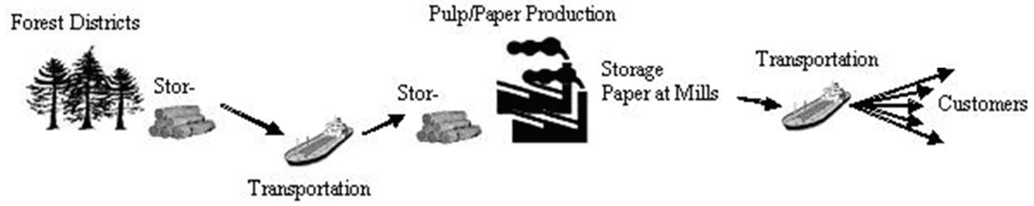

Fig. 1. Supply chain in pulp and paper industry.

2.2. Mathematical model

The model consists of storage cost, production/manufacturing cost and transportation cost. The objective function equation (1) minimizes the sum of the costs relative to storage, manufacture/production, and transport.

$$\textit{Minimize} \quad f(x) = C_{storage} + C_{manufacture} + C_{transport} \tag{1}$$

such that:

$$C_{manufacture} = \sum_{p=1}^{P}\sum_{t=1}^{T} C_p^P \left[J_{p,t+1} + \sum_{r=1}^{R} Z_{rpt} - J_{pt} \right] \tag{2}$$

$$C_{transport} = \sum_{r=1}^{R}\sum_{p=1}^{P}\sum_{t=1}^{T} C_{rp}^D Z_{rpt} + \sum_{m=1}^{M}\sum_{t=1}^{T} C_m^M \left\{ I_{m,t+1} + \sum_{p=1}^{P} \theta_{mp} \left[J_{p,t+1} + \sum_{r=1}^{R} Z_{rpt} - J_{pt} \right] - I_{mt} \right\} \tag{3}$$

$$C_{storage} = \sum_{r=1}^{R}\sum_{p=1}^{P}\sum_{t=2}^{T+1} H_{rp}^R K_{rpt} + \sum_{p=1}^{P}\sum_{t=2}^{T+1} H_p^P J_{pt} + \sum_{m=1}^{M}\sum_{t=2}^{T+1} H_m^M I_{mt} \tag{4}$$

subject to:

$$K_{rpt} + Z_{rpt} - K_{rp,t+1} \ge 0 \tag{5}$$

$$J_{p,t+1} + \sum_{r=1}^{R} Z_{rpt} - J_{pt} \ge 0 \tag{6}$$

$$\sum_{p=1}^{P} B_p \left[J_{p,t+1} + \sum_{r=1}^{R} Z_{rpt} - J_{pt} \right] \le \beta_t \tag{7}$$

$$\sum_{r=1}^{R}\sum_{p=1}^{P} W_p^P Z_{rpt} \le \omega_t^P \tag{8}$$

$$I_{m,t+1} + \sum_{p=1}^{P} \theta_{mp} \left[J_{p,t+1} + \sum_{r=1}^{R} Z_{rpt} - J_{pt} \right] - I_{mt} \ge 0 \tag{9}$$

$$\sum_{m=1}^{M} W_m^M \left\{ I_{m,t+1} + \sum_{p=1}^{P} \theta_{mp} \left[J_{p,t+1} + \sum_{r=1}^{R} Z_{rpt} - J_{p,t} \right] \right\} - I_{mt} \le \omega_t^M \tag{10}$$

where B_p :is the process time necessary to produce each unit of the p^{th} product; β_t: is the total capable time for producing at the the t^{th} period; C_{rp}^D : is the cost of delivering one unit of the p^{th} product from the manufacturer to the r^{th} retailer; C_m^M : is the cost of delivering one unit of the m^{th} raw material from the supplier to the manufacturer; C_p^P : is the cost of production of the p^{th} product; H_m^M : is the storage cost for each unit of the m^{th} raw material kept in the inlet stock of the manufacturer; H_p^P : is the storage cost of each unit of the p^{th} product kept in the outlet stock of the manufacturer; H_{rp}^R : is the storage cost of each unit of the p^{th} product kept in the r^{th} retailer (while transporting); I_{mt}: is the amount of the m^{th} raw material stored kept in the inlet stock of the manufacturer, at the beginning of the t^{th} period; J_{pt}: is the amount of the p^{th} product stored in the manufacturing sector, at the beginning of the t^{th} period; K_{rpt}: is the amount of the p^{th} product stored in the r^{th} retailer, at the beginning of the t^{th} period; W_m^M : is the weight of each unit of the m^{th} raw material; W_p^P : is the weight of each unit of the p^{th} product; ω_t^P : is the load limit for transporting products from manufacturer to retailers at the t^{th} period; ω_t^M : is the load limit for transporting materials from supplier to manufacturer at the t^{th} period; Z_{rpt}^M : is the amount of the p^{th} product sent from the manufacturer to the r^{th} retailer, at the t^{th} period; θ_{mp}: is the amount of the m^{th} raw material necessary to produce each unit of the p^{th} product.

Equation (5) and (6) indicates that both sales and production must be positive. In the same way, equation (9) indicates that the amount of raw material from forestry to manufacturer must be also positive. Equation (7) limits the production capacity to a given value. Equations (8) and (10) limit, respectively, the total weight of the transported products and raw materials. The approach adopted for this case study was formulated like an integer programming problem, in which the decision variables that compose vector x, to be optimized by the ABC methods, are: $I_{mt}(m = 1,2,..M;\ t = 2,3...,T)$, $J_{pt}(p = 1,2...,P;\ t = 2,3...,T)$, $K_{rpt}(r = 1,2...,R;\ p = 1,2...,P;\ t = 2,3...,T)$, $Z_{rpt}(r = 1,2...,R;\ p = 1,2...,P;\ t = 2,3...,T)$ *where* $I_{mt}, J_{pt}, K_{rpt}, Z_{rpt} \geq 0$.

3. BRIEF DESCRIPTION OF ABC

Artificial Bee Colony (ABC) simulates the intelligent foraging behaviour of a bee colony. ABC model comprises of three kinds of bees: employed, onlooker, and scout. The position of a food source represents a possible solution to the optimization problem and the nectar amount of a food source corresponds to the quality (fitness) of the associated solution. The number of the employed bees or the onlooker bees is equal to the number of food sources in the population. A comprehensive survey of ABC can be found in (Karaboga, 2012).

Steps of Artificial Bee Colony algorithm:

Initialization: Initialize the 2*SN* food sources using equation (11), evaluate them and move the employed bees on to the *SN* food sources with more nector amounts.

$$x_i^j = x_{\min}^j + rand()(x_{\max}^j - x_{\min}^j) \tag{11}$$

where $x_{\max}^j$ and $x_{\min}^j$ are upper and lower bounds of parameter j, respectively.

Employed Bee Phase: The employed bee explores the new candidate food sources around themselves from the old one in memory by using equation (12).

$$v_{ij} = x_{ij} + \phi_{ij}(x_{ij} - x_{kj}) \tag{12}$$

where v_{ij} is the new food source in the neighbor of employed bee; $j \in \{1, 2, \ldots, D\}$ (*D is the number of optimization parameters*). $k \in \{1, 2, \ldots, SN\}$ is randomly chosen index. Moreover, $k \neq i$. $Ø_{ij}$ is a random number between [-1, 1]. It controls the production of neighbor food sources around x_{ij} and represents the comparison of two food positions visible to a bee.

Onlooker Bee Phase: An onlooker bee evaluates the nectar information collected from all employed bees and chooses a food source with a probability related to its nectar amount. This probability is computed as:

$$p_i = \frac{fit_i}{\sum_{i=1}^{SN} fit_i} \tag{13}$$

where fit_i is the fitness value of the solution i proportional to the nectar amount of the food source in the position i. Onlooker bee produces a mutant solution using the same updated equation used by employed bee i.e. equation (12).

Scout Bee Phase: The abandoned position will be replaced with a new food source found by the scout. Assume that the abandoned source x_i, then the scout discovers a new food source to be replaced with x_i using equation (11).

Constrained ABC

For solving the constrained real parameter optimization problems suitable modifications can be made as per (Goldberg & Deb, 1991). In order to produce a candidate food position from the old one in memory, the ABC algorithm uses the following expression:

$$v_{ij} = \begin{cases} x_{ij} + \phi_{ij}(x_{ij} - x_{kj}), & if\ R_j \le MR \\ x_{ij}\ , & otherwise \end{cases} \tag{14}$$

where $k \in \{1, 2,..., SN\}$ is randomly chosen index such that it $k \neq i$. R_j is randomly chosen real number in the range [0,1] and $j \in \{1, 2,...,D\}$. *MR* (modification rate) is a control parameter that controls whether the parameter x_{ij} will be modified or not.

4. UABC (UPDATED FOOD POSITIONS IN ABC): PROPOSED VARIANT OF ABC

Like other evolutionary algorithms ABC also has some drawbacks which obstruct its performance. As per (Zhu & Kwong, 2010), it was observed that according to the solution search equation of ABC algorithm described by equation (12), the new candidate solution is generated by moving the old solution towards (or away from) another solution selected randomly from the population. However, the probability that the randomly selected solution is a good solution is the same as that the randomly selected solution is a bad one, so the new candidate solution is not promising to be a solution better than the previous one. On the other hand, in equation (12), the coefficient r_{ij} is a uniform random number in [-1, 1] and x_{kj} is a random individual in the population, therefore, the solution search dominated by equation (12) is random enough for exploration. As a conclusion, search equation described by equation (12) is good at exploration but is not so good at exploitation indicating that some added mechanism is needed to further improve the performance of ABC.

In the present study, we have used the concept of MMO proposed by (Chellapilla, 1998) in ABC, to enrich its searching capabilities. After making some suitable changes in notations, mutation in context of ABC may be defined as:

$$x'_{ij}(g) = x_{ij}(g) + \Delta x_{ij}(g) \tag{15}$$

where $x'_{ij}(g)$ is the new position obtained by adding a step size $\Delta x_{ij}(g)$ to the original position x_{ij}. The step size is noise sampled from some probability distribution, where the deviation of the noise is determined by a strategy parameter, σ_{ij}. Generally, the step size is calculated as:

$$\Delta x_{ij}(g) = \Phi(\sigma_{ij}(g))\eta_{ij}(g) \tag{16}$$

where $\Phi : \Re \to \Re$ is a function that scales the contribution of the noise, $\eta_{ij}(g)$. The mean mutation operator (MMO) is a linear combination of Gaussian and Cauchy distributions. In this case,

$$\eta_{ij}(g) = \eta_{N,ij}(g) + \eta_{C,ij}(g) \tag{17}$$

where $\eta_{N,ij} \sim N(0, 1)$ and $\eta_{C,ij} \sim C(0, 1)$. Deviations are calculated as:

$$\sigma_{ij}(g) = \frac{f(x_i(g))}{\sum_{l=1}^{SN} f(x_l(g))} \tag{18}$$

where *SN* is the population of Food source locations. The modification in the basic ABC algorithm is done by producing a new candidate food position from the old one in memory; using the following expression:

If (*rand* (0, 1) ≥ 0.5)

Then $v_{ij} = \begin{cases} x_{bestj} + r_{ij}(x_{ij} - x_{kj}), & if\ R_{ij} < MR, \\ x_{ij}, & otherwise, \end{cases}$

(19)

Else $v_{ij} = \begin{cases} x_{ij}', & if\ R_{ij} < MR, \\ x_{ij}, & otherwise, \end{cases}$

End If

where, $x_{best,j}$ is the individual having best fitness. From the above equation we can easily see that equal chances are given to both the conditions. After doing a series of experiments we observed that the value of MR = 0.4 is reasonably good for the optimization problems considered in this paper.

Handling of integer variables in UABC

The mathematical model used in this study is subject to integer restrictions. For dealing with integer variables we have rounded of the decision variables to nearest integer using *int* () function, a function for converting a real value to a closest integer value.

5. EXPERIMENTAL SETTINGS AND RESULT ANALYSES

Parameter Settings and Test Bed: The colony size (*SN*) is taken as 40; limit, maximum cycle numbers (*MCN*), and modification rate (*MR*) are considered as MCN/(2*SN), 6000 and 5.0e+05 respectively. 30 runs are taken to execute each test. All the algorithms have been executed on dual core processor with 1GB RAM. The programming language used is DEV C++. The random numbers are generated using inbuilt *rand* () function with same seed for every algorithm. We have tested the ABC algorithm and UABC in two groups of functions. The first group consists of basic constrained functions, and the second one on real time application.

Parameter Setting for Optimizing Supply Chain: The optimization of supply chain in pulp and paper industry was based on the following assumptions: all stocks (raw materials and products) are initially empty and there are M=3 raw materials, P=1 products, R=3 retailers and T=3 periods. The parameters of this simplified supply chain problem are optimized in this work, as follows:

– products demands D_{rpt}, at each period are forecasted as:
 D_{111}=80; D_{112}=60; D_{113}=70, D_{211}=60; D_{212}=75; D_{213}=65, D_{311}=80; D_{312}=70; D_{313}=90,
– Machine processing time, B_p: (B_1, B_2) = (1, 1); Allotted time for manufacturing, β_t: (β_1, β_2, β_3)=(800, 800, 800); Transportation cost from manufacture to retailers, $C^D_{rp}:\ (C^D_{11}, C^D_{21}, C^D_{31})$ = (1, 1, 4, 4); Transportation cost from supplier to manufacturer, $C^M_m:\ (C^M_1, C^M_2, C^M_3)$ = (3, 3, 2); Manufacture cost, $C^P_p:(C^P_i)$ = (20); Storage cost in the inlet stock, $H^M_m:(H^M_1, H^M_2, H^M_3)$ = (5, 8, 6); Storage cost in the outlet stock, $H^P_p:(H^P_1)$ = (4); Storage cost of products in the retailers, $H^R_{rp}:(H^R_{11}, H^R_{21}, H^R_{31})$ = (8, 4, 12); Raw material weight, $W^M_m:(W^M_1, W^M_2, W^M_3)$ = (3, 2, 2); Product weight, $W^P_p:(W^P_1)$ = (7); Load limit from supplier to manufacturer, $\omega^M_t:(\omega^M_1, \omega^M_2, \omega^M_3)$ = (5000, 5000, 5000); Load limit from manufacturer to retailers, $\omega^P_t:(\omega^P_1, \omega^P_2, \omega^P_3)$ = (3000, 3000, 3000); Amount of raw material used in products, $\theta_{mp}:(\theta_{11}, \theta_{21}, \theta_{31})$ = (1, 3, 2)

For all optimization algorithms, individuals are composed by the decision variables I_{mt}, J_{pt}, K_{rpt}, Z_{rpt}, which are rounded to the nearest integer, when computing the function f(x). Variables were allowed to span within the following ranges: $0 \le I_{mt} \le 10$; $0 \le J_{pt} \le 10$; $0 \le K_{rpt} \le 10$ (however $0 \le K_{212} \le 20$); and $0 \le Z_{rpt} \le 80$.

Basic Constrained Functions and results discussion: In order to assess the performance of the UABC algorithm, we considered constrained functions proposed in (Michalewicz & Schoenauer, 1996) and compared it with basic ABC and MO-ABC (Subotic, 2011).

***Table 1.** Simulation results for the constrained optimization problems.*

f(optimum)	Stat.	ABC	MO-ABC	AABC	*f*(optimum)	Stat.	ABC	MO-ABC	AABC
*g*01 (-15.000)	Mean	-15.000	-15.000	-15.000	*g*04 (-30665.538672)	Mean	-30665.539	-30665.539	**-30665.541**
	SD	0.000	0.000	0.000		SD	0.000	0.000	0.000
	Worst	-15.000	-15.000	-15.000		Worst	-30665.539	-30665.539	-30665.539
	Best	-15.000	-15.000	-15.000		Best	-30665.539	-30665.539	-30665.539
*g*02 (-0.803619)	Mean	-0.79241	-0.793506	**-0.799731**	*g*05 (5126.496714)	Mean	5185.714	5162.496	**5125.9462**
	SD	0.012	0.014	**0.025**		SD	75.358	**47.8**	52.192
	Worst	-0.749797	-0.744311	**-0.799476**		Worst	5438.387	**5229.134**	5232.174
	Best	-0.803598	-0.803605	**-0.803621**		Best	5126.484	5126.582	**5126.517**
*g*03 (-1.0005001)	Mean	-1	-1	**-1.00042**	*g*06 (-6961.813875)	Mean	-6961.814	-6961.814	-6961.814
	SD	0.000	0.000	0.000		SD	0.002	0.000	0.001
	Worst	-1	-1	**-1.00041**		Worst	-6961.805	**-6961.814**	-6961.813
	Best	-1	-1	**-1.00047**		Best	-6961.814	-6961.814	-6961.814

The results obtained in Table 1 using UABC are better or at par with the results obtained by original ABC algorithm and MO-ABC for constrained optimization problems. The *g*05 function illustrates that the UABC due to greater exploration capability, better best results are reached, but also the worst result is slightly worse than compared algorithm. The standard deviation for *g02* function is also inferior for the same reason. UABC reaches much better results for *g*02 and *g*03 function then the original ABC algorithm.

The simulation results for the considered benchmark functions are very close to their optimum solutions, hence there is no much space for improvements.

Results of Supply chain system and discussion: The best results obtained by ABC and UABC are presented in table 2. Both ABC and UABC responded well for all the runs. Further it is observed from the table 2 that proposed UABC outperformed ABC in terms of best, average and standard deviation

(Std. Dev.). The best simulated result obtained using proposed variant UABC i.e. *51,739.2* correspond to the values for the decision variables.

Table 2. *Simulation results of the optimized supply chain system and corresponding decision variables values.*

Algorithms	Best	Worst	Average	Std. Dev.
ABC	55,985.8	89,644.3	65,043.5	76,565.9
UABC	51,739.2	85,754.7	59,194.8	64,454.6
Decision Variables				
I_{mt}	J_{pt}	K_{rpt}	Z_{rpt}	
$I_{11} = 7$ $I_{12} = 6$ $I_{13} = 9$ $I_{21} = 5$ $I_{22} = 7$ $I_{23} = 7$ $I_{31} = 8$ $I_{32} = 6$ $I_{33} = 5$	$J_{11} = 9$ $J_{12} = 7$ $J_{13} = 8$	$K_{111} = 9$ $K_{112} = 7$ $K_{113} = 6$ $K_{211} = 7$ $K_{212} = 15$ $K_{213} = 8$ $K_{311} = 6$ $K_{312} = 7$ $K_{313} = 8$	$Z_{111} = 65$ $Z_{112} = 78$ $Z_{113} = 53$ $Z_{211} = 31$ $Z_{212} = 63$ $Z_{213} = 72$ $Z_{311} = 17$ $Z_{312} = 57$ $Z_{313} = 69$	
Costs				
Storage	Manufacturing		Transportation	
417	47593.2		3729	
Total Cost = 51,739.2				

6. CONCLUSIONS

Paper manufacturing units play an important role in Indian economy. In the present study, we have used UABC, a modified variant of ABC algorithm for solving a supply chain model for a pulp and paper industry. It is observed from the numerical results that the proposed method can deal efficiently with supply chain models subject to integer restrictions.

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ZMODYFIKOWANA PROCEDURA ROZMIESZCZENIA POŻYWIENIA W ALGORYTMIE SZTUCZNEJ KOLONII PSZCZÓŁ W ZASTOSOWANIU DO ZARZĄDZANIA ŁAŃCUCHEM DOSTAW

Streszczenie

Opisane w pracy badania dotyczą zarządzania łańcuchem dostaw przy zastosowaniu zmodyfikowanego algorytmu sztucznej kolonii pszczół (ang: Artificial Bee Colony - ABC), zwanego UABC (ang. Updated Artificial Bee Colony). Algorytm ten

wykorzystuje liniową kombinację rozkładów Gaussa i Cauchy'ego w celu uaktualnienia pozycji rozmieszczenia pożywienia. Optymalizacja modelu łańcucha dostaw jest problemem programowania całkowitoliczbowego lub problemem programowania mieszanego z ograniczeniami. Opracowany algorytm UABC uwzględnia te informacje. Analiza statystyczna algorytmu UABC, w porównaniu z trzema innymi algorytmami opartymi na ABC, wskazuje na jego wydajność i poprawność.

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