IMPACT: International Journal of Research in Business Management (IMPACT: IJRBM)
ISSN (E): 2321-886X; ISSN (P): 2347-4572
Vol. 4, Issue 5, May 2016, 99-108

INNOVATIVE APPLICATION OF OPTIMIZATION IN SUPPLY CHAIN MANAGEMENT

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ABSTRACT

The differential evolution approach has become a promising optimization technique in recent decades. It has been successfully applied to solve various problems in science and engineering fields; however, few applications have been addressed in the domain of supply chain management. In this paper, an improved DE approach is proposed for the aggregate planning problem in a supply chain. The approach comprises an improved DE variant with a winner-based constraint handling mechanism called the winner-based constrained differential evolution. To test the performance of the approach, it is verified and compared with most commonly used DE approaches. The experimental study shows that the winner-based constrained differential evolution possesses particular qualities in convergence, accuracy, and reliability for the aggregate planning problem in supply chains.

KEYWORDS: Supply Chain Management, Operations Management, Aggregate Planning, Differential Evolution

1. INTRODUCTION

Aggregate planning (AP) is an intermediate-range capacity planning. It aims to achieve a satisfactory production plan that will effectively utilize organization's resource, such as workforce, inventory and subcontract, over a specific time horizon ranged from 2 to 12 months for a given set of resources and constraints (Al-E-Hashem, Aryanezhad, & Sadjadi, 2012; Graves, 2002; Stevenson, 2009). Such planning problem usually involves one product or a family of products so that considering the problem from an aggregate viewpoint is justified. The AP problem has attracted considerable attention from both practitioners and academia. The pioneers of this research, Holt, Modigliani, and Simon (Holt, Modigliani, & Simon, 1955), first revealed the importance, obstacles and solutions of the problem in 1955. They formalize and quantify an AP problem by quadratic approximation to a criterion function involving the inventory, overtime, and employment. They also calculate the optimum solution of the problem in the form of a linear decision rule known as LDR model. The approach was applied to a paint factory to generate aggregate production plans. Hanssmann and Hess(Hanssmann & Hess, 1960)developed an AP model focused on minimizing the total cost of regular payroll, overtime, hiring, layoff, inventory and shortage which incurred over a given time horizon. Rakes et al. (Rakes, Franz, & James Wynne, 1984) proposed a chance-constrained goal programming approach to the problem. It is a special case of stochastic planning to production scheduling which incorporates probabilistic product demand requirements. An overview of the researches was given by Nam and Logendran (Nam & Logendran, 1992). They compile the research literatures which consist of 140 articles from 17 journals and 14 books, presenting classification scheme and various techniques into a broad framework. The techniques ranged from simple graphical methods to sophisticated heuristics can be broadly categorized into two types: those that guarantee an optimum solution and those that do not.

In recent decades, since the great development in heuristics and modeling approaches, there is a trend in research communities to solve AP problems by modern heuristic optimizers. Paiva and Morabito(Paiva & Morabito, 2009) proposed an optimization model to support decisions in the AP problem of the sugar and ethanol milling factory. The model is a mixed integer programming formulation based on the industrial process selection method and production lot-sizing model. Sillekens et al. (Sillekens, Koberstein, & Suhl, 2011) presented a mixed integer linear programming model for the AP problem of flow shop production lines in automotive industry. In contract to traditional approaches, the model considers discrete capacity adaptions which originated from technical characteristics of assembly line, work regulation and shift planning. Its solution framework containing different primal heuristics and preprocessing techniques is embedded into a decision support system. Zhang et al. (Zhang, Zhang, Xiao, & Kaku, 2012)presented a mixed integer linear programming model which characterizesan AP problem with capacity expansion in a manufacturing system. The system includes multiple activity centers, and they use a heuristic method based on capacity shifting with linear relaxation to optimize the model. Ramezanian et al. (Ramezanian, Rahmani, & Barzinpour, 2012) introduced an AP problem which includes a multi-period, multi-product, and multi-machine with setup decisions. They develop a mixed integer linear programming model and use Genetic Algorithm (GA) and Tabu search for solving the model.

The differential evolution (DE) algorithm is a simple yet powerful evolutionary algorithm for optimization problems. It has become a promising heuristic technique in recent decades. The algorithm was proposed by Storn and Price in 1995 while trying to solve the Chebyshev polynomial fitting problem (Storn & Price, 1995). DE is a powerful stochastic global optimizer that stems from the genetic annealing algorithm also developed by Price. With a randomly initialized population, DE employs simple mutation and crossover operators to generate new offspring, and then utilizes a selection technique to determine whether the offspring will replace their parents into next generation. It has been successfully applied to solve various problems in the scientific and engineering field, such as pattern recognition (Swagatam Das & Konar, 2009; Maulik & Saha, 2009), power dispatch (Chiou, 2009; Varadarajan & Swarup, 2008), control systems(Iruthayarajan & Baskar, 2009; Tang, Xue, & Fan, 2008), and others (S. Das & Suganthan, 2011). Now that DE has been proved to be a very efficient and robust technique.

In the fact of many successful DE applications have been addressed in the scientific and engineering field, few works have been done in the management field, especially in the area of aggregate planning. Besides, in the course of solving AP problems by DE, we discover a better DE strategy that possesses particular performance for the problem than commonly used DE approaches. Moreover, DE also lacks a good constraint handling mechanism to deal with such a highly constrained AP problem. Therefore, in this paper, for solving AP problems a novel DE approach called a winner-based constrained differential evolution, which comprises an improved DE strategy and a constraint handling mechanism called the winner-based constraint handling mechanism, is proposed. After experimental studies, the results show that the approach possesses particular performance in convergence, accuracy, and reliability for solving AP problems than the most commonly used DE approaches.

The rest of the paper is organized as follows: section 2 presents full details of the winner-based constrained differential evolution, comprising the improved DE strategy and the winner-based constraint handling mechanism for solving AP problems. The evaluation experiments are displayed in section 3, and some conclusions, research findings and managerial implications are addressed in the final section.

2. THE WINNER-BASED CONSTRAINED DE APPROACH

To enhance the local search ability and to stably accelerate the convergence speed for DE to highly constrained AP problems, an improved DE mutation strategy introducing an exponential probability distribution is involved. The scale factor *F* is randomly generated by introducing an appropriate exponential probability distribution, which can provide a good compromise between the probability of having a large number of small perturbations and a small probability of having large perturbations. The density function of the exponential probability distribution is given in (1). In this function, it is obvious that we can control the variance by changing the location parameter *a* and the scale parameter *b*. The process of generating the scale factor *F* by the exponential probability distribution function is presented in Algorithm 1.

$$f(x)=\frac{1}{2b}\exp(-\frac{|x-a|}{b}),\quad -\infty<x<\infty,\quad a,b>0 \tag{1}$$

Algorithm 1: Generating the Scale Factor *F* by the Exponential PDF

Table 1

1	*u1 = rand[0, 1] ;*	% uniform random number [0, 1]
2	*u2 = rand[0, 1] ;*	
3	**if** *u1 > 0.5*	
4	*x = a + b*ln(u2) ;*	% Natural logarithm
5	**else**	
6	*x = a - b*ln(u2) ;*	
7	**end**	
8	$F_{\exp}$ = *abs(x) ;*	% absolute value

To handle constraints for highly constrained A P problems, we propose a mechanism called the winner-based constraint handling mechanism. The mechanism is a decision-making scheme based on the score of a well-defined scoring function to decide a winner among candidate solutions within a constrained search space, as follows:

An AP problem with many equality and inequality constraints can be formally expressed as the formulation:

Minimize $f(x)$ (2)

subject to $g_i(x)\le 0$, $i=1,\ \dots,\ p$ (3)

$h_j(x)=0$, $j=1,\ \dots,\ q$ (4)

$\forall\ x\ge 0$

The boundaries, equality constraints in (4), can be transformed into the form of inequality constraints:

$$|h_j(x)|-\varepsilon\le 0 \tag{5}$$

where ε is the tolerance of a very small positive value allowed. Therefore, all constraints can be expressed as:

$$l_k(x)\le 0,\ k=1,2,\dots,r \tag{6}$$

Then a closeness function, defined by(7), can be incorporated to measure the closeness of a solution to the feasible region of a constrained problem. A solution *x* of the problem is called a candidate. If the function value of a candidate compared with others is larger, it can be regarded as closer to the feasible region than the others.

$$c(x) = \sum_{k=1}^{r} \min(0, -l_k(x)) \tag{7}$$

Thus, a scoring function measuring the degree of candidates in the winner-based constraint handling mechanism can be defined by:

$$score(x) = \begin{cases} c(x) & \text{if } c(x) < 0 \\ \exp(-f(x)) & o.w. \end{cases} \tag{8}$$

Where $score(x) \leq 1$, $c(x)$ is the closeness function, $f(x)$ the objective function, and exp(x) the exponential transformation function.

The scoring function is used as decision-making criteria. It selects a winner into next generation which has a highest score against other candidates. If the score of a candidate is less than 0, which means the candidate violates at least one constraint and is classified as infeasible. After iterations in the evolving process, the winner will tend to feasible region rather than infeasible and to a good solution gradually. In addition, the violations of the objective and constraints are considered, leaving the annoying penalty parameter which needs to be fine-tuned while using the penalty function approach.

3. EXPERIMENTAL STUDY

3.1 Test Experiments

In this section, the performance of the winner-based constrained differential evolution for solving constrained AP problems is presented. The approach is verified and compared with three most commonly used DE approaches, DE/rand/1, DE/best/1 and DE/target-to-best/1. Some test instances of the AP problem, from small-sized to large-sized, are given from Red Tomato Tools, a manufacturer of gardening equipment in a supply chain with highly fluctuated demand requirements and constraints in Mexico, illustrated in (Chopra & Meindl, 2007; Wang & Yeh, 2014). All of the test instances, DE approaches, and the winner-based constraint handling mechanism are coded by MATLAB R2012a and executed on a laptop PC with Intel Core 2 Dual 2.0 GHz CPU, 4 GB RAM, and 64-bit Windows 7 operating system. To establish the benchmark of comparative performance, they are also coded by LINGO optimization solver to present global optimum as lower bound. We also define a quality measurement called the percentage of deviation, denoted as %*Dev* and expressed in (9), to present the diversity of experimented outcome with corresponding lower bound. Where in (9), BOV is the best objective value and LB the lower bound.

$$\%Dev = \frac{BOV - LB}{LB} \times 100\% \tag{9}$$

In these DE experiments, as suggested, the population size of a trial is set to 8 times of the dimensionality of the test instance. The crossover rate *Cr* and the scale factor *F* are set to 0.9 and 0.85 respectively. While in the improved DE strategy, we use the exponential probability distribution function with the parameters of *a*=0 and *b*=0.5 to generate the values of the scale factor *F*. Termination criteria of a trial are set to either less than 5% of closeness with its corresponding lower bound or reaching to 5,000 iterations. The experimental results of an instance for each DE approach are collected from 10 trials of execution. The report statistics are the stop iteration, best objective value, mean and standard deviation of the best objective values, the iteration at which the score starts greater than 0, and the percentage of deviation. The convergent variations of the best objective values and the scores over iterations for each approach are presented from Figure 1 to Figure 4. The report statistics are also shown in Table 1 and Table 2.

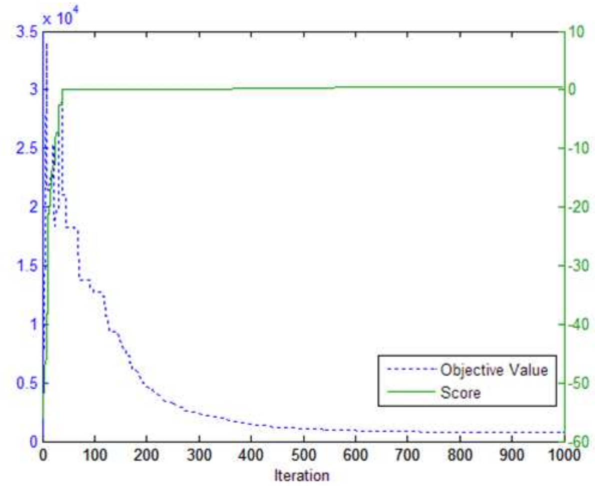

Figure 1: Convergent Variations Over Iterations for the Proposed Approach

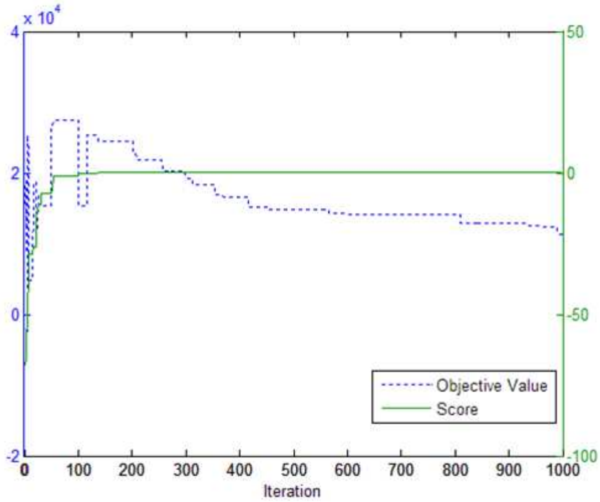

Figure 2: Convergent Variations Over Iterations for DE/Rand/1

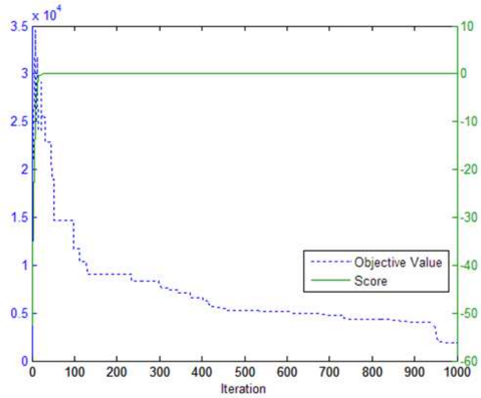

Figure 3: Convergent Variations Over Iterations for DE/Best/1

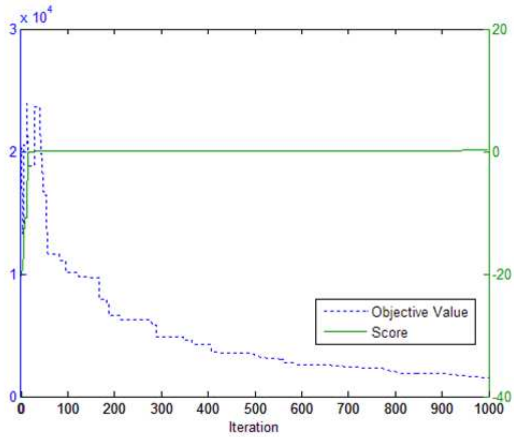

Figure 4: Convergent Variations Over Iterations for DE/Target-to-best/1

Table 1: Report Statistics

	Experiment	**1**	**2**	**3**	**4**	
	Periods	3	6	9	12	
	Worker Type	1	2	3	4	
	Num.of Para.	24	48	72	96	
	Num.of Constr.	12	42	90	156	
DE Strategy	**LB**	152	304	456	612	**Average**
Improved DE	Iter. (Stop)	1,162	2,457	3,291	4,523	2,858
	Best	158	315	473	635	395
	Mean	1,479	4,314	5,173	5,650	4,154
	Std.Dev	2,787	7,943	10,827	13,465	8,755
	Iter. (Score>0)	46	73	143	156	105
	%Dev	3.8%	3.6%	3.7%	3.8%	3.7%
DE/rand/1	Iter. (Stop)	5,000	5,000	5,000	5,000	5,000
	Best	2,488	32,594	81,402	102,693	54,794
	Mean	5,955	36,120	NaN	NaN	-
	Std.Dev	3,737	5,386	NaN	NaN	-
	Iter. (Score>0)	37	757	>5,000	>5,000	-
	%Dev	1,536.6%	10,621.8%	17,751.2%	16,679.9%	11,647.4%
DE/best/1	Iter. (Stop)	3,227	5,000	5,000	5,000	4,557
	Best	158	2,036	12,344	31,920	11,615
	Mean	1,517	10,248	28,301	51,237	22,826
	Std.Dev	2,793	10,041	13,861	16,133	10,707
	Iter. (Score>0)	17	96	223	555	223
	%Dev	3.9%	569.7%	2,607.0%	5,115.7%	2,074.1%
DE/target-to-best/1	Iter. (Stop)	3,045	5,000	5,000	5,000	4,511
	Best	157	1,534	9,752	24,527	8,993
	Mean	1,474	8,822	25,414	44,233	19,986
	Std.Dev	2,567	8,443	13,853	15,340	10,051
	Iter. (Score>0)	17	74	207	598	224
	%Dev	3.5%	404.8%	2,038.5%	3,907.7%	1,588.6%

Table 2: Comparative Performance

DE Strategy	Iterations	Best	Mean	Std.Dev	Iter.(Score>0)	%Dev
Improved DE	100%	100%	100%	100%	100%	100%
DE/rand/1	175%	13,865%	-	-	-	313,523%
DE/best/1	159%	2,939%	549%	122%	213%	55,830%
DE/target-to-best/1	158%	2,275%	481%	115%	214%	42,762%

3.2 Experiment Discussion

These experimental results show that the winner-based constrained differential evolution provides remarkable performance for solving the AP problem than those commonly used DE approaches, discussed as follows:

- The convergent variations over iterations, from Figure 1 to Figure 4, show that at the beginning of iteration, the best objective values for each DE approach have higher degree of volatility. Even after more iteration the best objective value has reached a small value, it is still infeasible, because the score is still less than 0, which means at least one constraint is still violated. At this stage, the winner-based constraint handling mechanism will keep good guiding, forcing the DE process substantially explore better solutions toward the feasible region quickly.
- After further iteration, the best objective value can be soon evolving into the feasible region because the score is turning into greater than 0. The winner-based constraint handling mechanism will handle the DE process exploiting better solutions without escaping from the feasible region, leading the best objective value stably and gradually evolving toward the global optimum. It is the feature of the winner-based constraint handling mechanism.
- In these figures and tables, all DE approaches can explore into the feasible region except DE/rand/1. The reason may be attributed to the great randomness of the approach which needs more efforts to explore in a highly constrained and large multi-dimensional space. That may limit the effectiveness and ability of its exploration. Besides, the improved DE strategy can explore and evolve into the feasible region better than others to a large degree. It is at about 105 iterations in average, better than the other DE approaches: DE/best/1 at 223 iterations, DE/target-to-best/1 at 224, and DE/rand/1 is the worst. The performance of the improved DE strategy for exploring the feasible region is times better than DE/best/1 (213%) and DE/target-to-best/1 (214%) in average (see Table 2), especially to large-sized problems (see Table 1).
- After evolving into the feasible region, the improved DE strategy will quickly and accurately exploit better solutions toward the global optimum in less iteration, at 2,858 iterations in average. It is also superior to the others: DE/best/1 is at 4,557, DE/target-to-best/1 at 4,511, and DE/rand/1 is still the worst. The performance of the improved DE strategy for exploiting the best objective value is better than DE/rand/1 (175%), DE/best/1 (159%) and DE/target-to-best/1 (158%) in average. It is worth mentioning that the improved DE strategy can explore inside the acceptance level of corresponding lower bound in less than 5,000 iterations for all size of the problems, while other DE approaches can only do for small-sized problems. We conclude that the improved DE strategy gains a good convergence to the optimum than others.
- Apparently, other statistics in Table 2, Best, Mean, Std. Dev, and *%Dev*, have also shown that the improved DE

strategy with the winner-based constraint handling mechanism gains greater performance than the other 3 DE approaches.

There fore, we can conclude that the improved DE strategy with the winner-based constraint Handling mechanism possesses particular quality in convergence, accuracy, and reliability for solving the AP problem than the Most commonly used DE approaches of DE/rand/1, DE/best/1, and DE/target-to-best/1.

4. CONCLUSIONS

In this paper, we first explore the importance of the AP problem, from early precursors to contemporary researches. Some significant researches and applications are also presented. In the next context, the full details of the winner-based constrained differential evolution, an improved DE strategy with constraint handling mechanism called the winner-based constraint handling mechanism, are introduced. In order to test the performance of the approach for solving constrained AP problems, it is verified and compared with three commonly used DE approaches, DE/rand/1, DE/best/1 and DE/target-to-best. Some test instances, from small-sized to large-sized, illustrated in a supply chain are given for the evaluation. The test results show that the winner-based constrained differential evolution possesses particular quality in convergence, accuracy, and reliability for solving AP problems than the most commonly used DE approaches of DE/rand/1, DE/best/1, and DE/target-to-best/1.

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