DEVELOPING NEW CHARGED SYSTEM SEARCH-BASED ALGORITHM: APPLICATION IN THE TIME-COST TRADE-OFF PROBLEMS

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ABSTRACT

The trade-off between the total cost and project duration is one of the most important parameters of construction project planning. There are various methods to optimize time-cost trade-off problems. Mathematical programming models as one type of them cannot solve large and complex networks effectively. On the other hand, although the meta-heuristics algorithms in many cases can find a complete set of solutions but to optimize the time-cost trade-off problems in very massive construction projects they need to spend a lot of time, so existence a powerful algorithm with higher convergence rate is necessary. In this paper new procedures MAWA-CSS and SMOCSS are introduced to generalize the well-known CSS algorithm for solving TCTP optimization problem and all multi-objective optimization problems in discrete and continuous search space. The overall structure of SMOCSS algorithm is similar to the MOPSO and to determine the Charge magnitude of particles a new simple method is introduced. The proposed method is examined for different test functions and the results are compared to the results of two well-known multi-objective algorithms (NSGA-II and MOPSO). In addition, two example of time-cost optimization problem (Feng and Zheng network with 18 and 7 activities respectively) are used to evaluate the performance of the proposed algorithms. The results indicate that the SMOCSS algorithm has the ability to find out the optimal solution and define the Pareto front as well in reasonable time. Hence the proposed approach in this paper is much adaptive and suitable for tackling TCTP, which is useful and beneficial for decision-making on the trade-off between project duration and total cost.

Keywords: *Time-Cost Trade-off Problems (TCTP), multi-objective optimization, meta-heuristics algorithms, Charged System Search (CSS)*

INTRODUCTION

The complexities and difficulties of a construction project causes changes in costs and timing of the project in the implementation phase. With the rapid expansion of the use of various systems project delivery, time is a determining factor in the evaluation of tenders and the manufacturing process. Therefore, construction managers not focus just on reducing costs but the project execution time is also so important. Forasmuch the compression of time will inevitably lead to a gradual increase in direct costs of the project, in project management, achieving optimal time-cost of the project becomes very important [1-3].

Several mathematical models such as linear programming [4, 5], integer programming, or dynamic programming [2, 6, 7] and LP/IP hybrid models are used to solve TCTPs [8, 9]. These methods are not suitable for large scale projects and cannot find all possible solutions [10]. Because of the population-based

nature of multi-objective evolutionary algorithms and their ability to find multiple optima simultaneously [11, 12], several different algorithms have been suggested in recent years to solve TCTP which can include Non-Dominated Sorting Genetic Algorithm (NSGA-II) [3, 10] Particle Swarm Optimization (PSO) [13], Adaptive Weighted Approach (AWA) and etc. [14-16]. In this study, the main contribution is on introducing different multi-objective CSS algorithms that, in addition to simplicity, they are capable on finding global optimum solutions and have high convergence rate.

The charged System Search (CSS) is one of the recently introduced single-objective optimization algorithm which have been used in science and engineering optimization problems successfully. This method mixes the governing motion from Newtonian mechanics and the governing Coulomb law from physics. In the CSS algorithm, each possible solution corresponds to a charged particle (CP) which can impose an attractive electric force on other CPs according to Coulomb's law. The next position of each CP is determined by Calculating the resultant forces acting on the CP and applying the kinematic equations [17-19]. The results of this algorithm compared with each other and with some other well-known multi-objective optimization methods. Also we will use the well-known these approaches to solve time-cost problem.

PRELIMINARIES

BASIC CONCEPTS IN MULTI-OBJECTIVE OPTIMIZATION MOO

For better understanding of the Multi-Objective Problems (MOPs), acquaintance with the following concepts are necessary [20]:

General Multi-objective Optimization Problem: The aim in a multi-objective optimization for minimization problem is finding a vector $x = (x_1, x_2, \dots, x_n)$ which satisfies k inequality constraints as:

$$q_i(x) \leq 0 \quad (i = 1, 2, \dots, k) \quad (1)$$

and l equality constraints:

$$h_i(x) = 0 \quad (i = 1, 2, \dots, l) \quad (2)$$

and minimizes the vector function

$$\text{Min}_{x \in \Omega} F(x) = \{f_1(x), f_2(x), \dots, f_m(x)\} \quad (3)$$

Where m is the number of objectives and Ω is a set of the decision vector.

Pareto Dominance: A vector $u = (u_1, u_2, \dots, u_n)$ dominates vector $v = (v_1, v_2, \dots, v_n)$ (denoted by $u < v$) if and only if u is partially less than v , i.e.,

$$\forall i \in \{1, 2, \dots, n\}, u_i \leq v_i \wedge \exists i \in \{1, 2, \dots, n\} : u_i < v_i. \quad (4)$$

Pareto Optimal: A solution $x \in \Omega$ is Pareto Optimal with respect to Ω if and only if there is no $x' \in \Omega$ for which $v = (f_1(x'), f_2(x'), \dots, f_n(x'))$ dominates $u = (f_1(x), f_2(x), \dots, f_n(x))$.

Pareto Optimal Set: For a given MOP, $F(x)$, the Pareto Optimal Set, P , is defined as $P = \{x \in \Omega \mid \neg \exists x' \in \Omega F(x') < F(x)\}$.

Pareto Optimal Front: For a given MOP, $F(x)$, and Pareto Optimal Set, P , the Pareto Front PF is defined as $PF = \{u = F(x) \mid x \in P\}$.

A solution is said to be Pareto Optimal if it is not dominated by any other solutions in the search space, also termed as non-dominated solution. In this paper, we distinguish the real Pareto Optimal front, termed PF_{real} , and the final set of non-dominated solutions obtained by a multi-objective optimization algorithm, termed $PF_{algorithm}$ as defined by the aim of the multi-objective optimization algorithms is to find a well uniformly distributed $PF_{algorithm}$ that approximates PF_{real} as close as possible.

CHARGED SYSTEM SEARCH

Charged System Search (CSS) algorithm, introduced by Kaveh and Talatahari [17], is based on electrostatic and Newtonian mechanics laws. In the CSS algorithm, charged particles (CPs) are assumed to be the candidate solutions. Charged particle are affected by the electric field that created by other particles. The amount of force exerted on each CP, are obtained using the electrostatic rules. Also, the motion of each CP is determined by the rules of Newtonian mechanics and the charge magnitude of each particle will be determined according to the value of the objective function [17-19]. Fig. 1 shows the pseudo-code of the CSS algorithm.

```

Initialize an array of charged particles (CPs) randomly
The initial velocities of these particles are taken as zero
While iteration < max iteration do
  For each particle
    ► Calculate charge magnitude:
      
$$q(i) = \frac{fit_{worst} - fit(i)}{fit_{worst} - fit_{best}}$$

    ► Calculate resultant force:
      
$$F_j = k_e q_j \sum_{i, i \neq j} \left( \frac{q_i}{a^3} r_{ij, i_1} + \frac{q_i}{r_{ij}^2} r_{ij, i_2} \right) \frac{X_i - X_j}{\|X_i - X_j\|}, \quad \begin{cases} i = 1, 2, \dots, N \\ i_1 = 1, i_2 = 0 \leftrightarrow r_{ij} < a \\ i_1 = 0, i_2 = 1 \leftrightarrow r_{ij} \geq a \end{cases}$$

       $r_{ij}$  is Euclidean distance between  $i$ th and  $j$ th CP
    ► Calculate new position and velocity:
      
$$X_{j, new} = r_{j1} \cdot k_a \cdot \frac{F_j}{q_j} + r_{j2} \cdot k_v \cdot V_{j, old} + X_{j, old}$$

      
$$V_j = X_{j, new} - X_{j, old}$$

       $r_{j1}$  and  $r_{j2}$  are random vectors in (0,1)
       $k_a$  and  $k_v$  are constant numbers
  End For
End While

```

Fig. 1: pseudo-code of the CSS algorithm.

TCTP PROBLEM FORMULATION

In the trade-off between the total cost and project duration problems (TCTP), there are twin objectives to be minimized: the project time and its cost. In a project, a two-objective optimization problem should be solved as follows:

$$\begin{cases} \min & T \\ \min & C \end{cases} \quad (5)$$

Where T is the total project time and C is the total project cost that they are defined as:

$$\begin{cases} T = \max_{L_k \in L} \left[\sum_{i \in L_k} t_i^{(k)} x_i^{(k)} \right] \\ C = \sum_{i \in A} dc_i^{(k)} x_i^{(k)} + T \times ic_i^{(k)} \end{cases} \quad (6)$$

Where A is the number of activities, $t_i^{(k)}$ represents the duration of activity i when performing the k th option, $x_i^{(k)}$ stands for the index variable of activity i when performing the k th option. If $x_i^{(k)} = 1$ then the activity i perform the k th option. The sum of index variables of all options should be equal to 1. L_k means the activity sequence on the k th path, and $L_k = \{i_{1k}, i_{2k}, \dots, i_{nk}\}$ where i_{jk} represents the sequence number of activity j on the k th path. L stands for the set of all paths of a network, and $L = \{L_k, k=1, 2, \dots, m\}$, where m symbolizes the number of all paths of a network. $dc_i^{(k)}$ and $ic_i^{(k)}$ represent the direct and indirect cost of activity i when performing the k th option, respectively [3, 13, 16].

NEW SIMPLE MULTI-OBJECTIVE CHARGED SYSTEM SEARCH (SMOCSS)

Due to the high convergence and large capability of CSS algorithm [17] we produced a new simple multi-objective optimization algorithm based on CSS algorithm (SMOCSS) that, in addition to simplicity, is capable of finding global optimum solutions and have high convergence rate [21-23]. The flowchart of this algorithm is shown schematically in Fig.2.

Fig.2: flowchart of SMOCSS algorithm

CHARGED SYSTEM SEARCH FOR MODIFIED ADAPTIVE WEIGHT APPROACH (MAWA-CSS-TCTP)

TCTP problem is a multi-objective optimization problem. One positive trend to solve this problem is Modified Adaptive Weight Approach [16]. In this paper based on Charged System Search algorithm and modified adaptive weighting method a model is developed and pareto front is achieved. The main steps of MAWA-CSS algorithm for TCTP are described as follows:

- 1) Randomly generation of initial solutions.
- 2) Computing the project duration and total cost from Eq.2.

- 3) Choosing the dominant answers and adding to the Pareto solution set
- 4) Calculating the alternative fitness value as:

$$f(X) = w_t \frac{Z_t - Z_t^{\min} + \gamma}{Z_t^{\max} - Z_t^{\min} + \gamma} + w_c \frac{Z_c - Z_c^{\min} + \gamma}{Z_c^{\max} - Z_c^{\min} + \gamma} \quad (11)$$

Which $Z_t^{\min}$ and $Z_t^{\max}$ as the minimal value and maximal value for the objective of duration respectively, $Z_c^{\min}$ and $Z_c^{\max}$ as the maximal value and minimal value for the objective of cost respectively, w_t and w_c are adaptive weight for the criterion of time and cost respectively that can be calculate by considering this conditions as:

$$\left\{ \begin{array}{l} \text{if } Z_t^{\min} = Z_t^{\min} \text{ and } Z_c^{\min} = Z_c^{\min} \\ \quad w_t = w_c = 0.5 \\ \text{else if } Z_t^{\min} \neq Z_t^{\min} \text{ and } Z_c^{\min} = Z_c^{\min} \\ \quad w_t = 0.9, \quad w_c = 0.1 \\ \text{else if } Z_t^{\min} = Z_t^{\min} \text{ and } Z_c^{\min} \neq Z_c^{\min} \\ \quad w_t = 0.1, \quad w_c = 0.9 \\ \text{else if } Z_t^{\min} \neq Z_t^{\min} \text{ and } Z_c^{\min} \neq Z_c^{\min} \\ \quad v_t = \frac{Z_t^{\min}}{Z_t^{\max} - Z_t^{\min}}, \quad v_c = \frac{Z_c^{\min}}{Z_c^{\max} - Z_c^{\min}} \\ \quad w_t = \frac{v_t}{v_t + v_c}, \quad w_c = \frac{v_c}{v_t + v_c} \\ \text{end} \end{array} \right.$$

- 5) Determine charge magnitude for all the particles in population as:

$$q_i = \frac{fit(i) - fit_{worst}}{fit_{best} - fit_{worst}}, \quad i = 1, 2, \dots, N \quad (12)$$

Where *fitbest* and *fitworst* are the so far best and the worst fitness of all particles; *fit(i)* represents the objective function value or the fitness of the agent *i*, and *N* is the total number of particles.

- 6) Initialize the F vector (resultant force vector acted on each particle) and determine the resultant force exerted to each particle.
- 7) Compute the new position and velocity of each particle.
- 8) Maintain the particles within the search space [22].
- 9) Repeating step 2 to step 8 until the generated Pareto solutions are repeated and there is no new solution in the generated set.

NUMERICAL EXAMPLES

PERFORMANCE METRICS

In order to provide a quantitative assessment for the performance of an MO optimizer, three issues are often taken into consideration [24]:

- a) The distance of the resulting non-dominated set to the Pareto-optimal front should be minimized.

b) A good (in most cases uniform) distribution of the solutions found is desirable. The assessment of this criterion might be based on a certain distance metric.

c) The extent of the obtained non-dominated front should be maximized, i.e., for each objective, a wide range of values should be covered by the non-dominated solutions.

Comparative studies performed by researchers such as [23-26] made use of a suite of unary performance metrics pertinent to the optimization goals of proximity, distribution, and diversity. In this paper, three different qualitative measures are utilized.

Generational distance (GD) is a measure of the distance between the true (PF_{real}) and generated Pareto front ($PF_{algorithm}$). This metric of individual distance representing the distance is given by

$$GD = \sqrt{\frac{1}{n_{pf}} \sum_{i=1}^{n_{pf}} d_i^2} \quad (13)$$

Where n_{pf} is the number of members in $PF_{algorithm}$ and d_i is the Euclidean distance between the i th member in $PF_{algorithm}$ and its nearest member in PF_{real} . A smaller value of GD implies better convergence.

The metric of spacing (S) gives an indication of how evenly the solutions are distributed along the discovered Pareto-front:

$$S = \sqrt{\frac{1}{n_{pf}} \sum_{i=1}^{n_{pf}} (d_i - \bar{d})^2} \quad , \quad \bar{d} = \frac{1}{n_{pf}} \sum_{i=1}^{n_{pf}} d_i \quad (14)$$

Where n_{pf} is the number of members in $PF_{algorithm}$ and d_i is the Euclidean distance (in the objective space) between the i th member in $PF_{algorithm}$ and its nearest member in PF_{real} . A smaller value of S implies a more uniform distribution of solutions in $PF_{algorithm}$.

The metric of maximum spread (MS) measures how “well” the PF_{real} is covered by the $PF_{algorithm}$ through hyper-boxes formed by the extreme function values observed in the PF_{real} and $PF_{algorithm}$. It is defined as:

$$MS = \left(\frac{1}{m} \sum_{i=1}^m \left(\frac{\min(f_i^{max}, F_i^{max}) - \max(f_i^{min}, F_i^{min})}{F_i^{max} - F_i^{min}} \right)^2 \right)^{0.5} \quad (15)$$

Where m is the number of objectives, f_i^{max} and f_i^{min} are the maximum and minimum of the i th objective in $PF_{algorithm}$, respectively, and F_i^{max} and F_i^{min} are the maximum and minimum of the i th objective in PF_{real} , respectively. A larger value of MS implies a better spread of solutions.

TEST PROBLEMS

Four benchmark problems ZDT1, ZDT3, FON and POL are selected to examine the performance of the proposed algorithm. The test problems are detailed in table 1 [26-29].

Table.1: Benchmark test problems ZDT1, ZDT3, FON and POL

Test problem	Mathematical formulas	Range of variables	Number of variables
ZDT1	$\begin{cases} f_1(x) = x_1 \\ \min \left\{ f_2(x) = g(x) \left[1 - \sqrt{\frac{x_1}{g(x)}} \right] \right\}, \quad g(x) = 1 + \frac{9}{n-1} \sum_{i=2}^n x_i \end{cases}$	$0 \leq x \leq 1$	30

ZDT3	$\min \begin{cases} f_1(x) = x_1 \\ f_2(x) = g(x) \left[1 - \sqrt{\frac{x_1}{g(x)}} - \frac{x_1}{g(x)} \sin(10\pi x_1) \right] \end{cases}$	$0 \leq x \leq 1$	30
FON	$\min \begin{cases} f_1(x) = 1 - \exp\left(-\sum_{i=1}^2 (x_i - \frac{\sqrt{2}}{2})^2\right) \\ f_2(x) = 1 - \exp\left(-\sum_{i=1}^2 (x_i + \frac{\sqrt{2}}{2})^2\right) \end{cases}$	$-2 \leq x \leq 2$	2
POL	$\min \begin{cases} f(x) = 1 + (A_1 - B_1)^2 + (A_2 - B_2)^2 \\ f(x) = (x_1 + 3)^2 + (x_2 + 1)^2 \\ A_1 = 0.5 \sin 1 - 2 \cos 1 + \sin 2 - 1.5 \cos 2 \\ A_2 = 1.5 \sin 1 - \cos 1 + 2 \sin 2 - .5 \cos 2 \\ B_1 = 0.5 \sin(x_1) - 2 \cos(x_1) + \sin(x_2) - 1.5 \cos(x_2) \\ B_2 = 1.5 \sin(x_1) - \cos(x_1) + 2 \sin(x_2) - 0.5 \cos(x_2) \end{cases}$	$-\pi \leq x_1, x_2 \leq \pi$	2

CASE STUDY IN TCTP

In this paper we will use multi-objective CSS algorithms mentioned in next sections to solve two well-known time-cost optimization problems named as the Feng network activities and the Zheng network activities. The Feng network with 18 activities is one of the most well-known examples for time-cost optimization problem that has attracted the attention of many researchers [3]. Configuration and activities network options of Feng network are shown in Fig. 3 and Table 2 respectively. In addition to Feng activities network, another activities network with 7 activities introduced by Zheng considered as second example. Configuration and activities network options of Zheng network are shown in Fig. 4 and Table 3 respectively [10].

Fig. 3: Configuration of Feng network activities

Table 2: Time, Cost, Number of execute options and Prerequisites of activities of Feng network

No	Pr	Op	Ti	Cost	No	Pr	Op	Ti	Cost	No	Pr	Op	Ti	Cost
1	-	1	14	2400	7	5	1	9	30000	13	3	1	14	4000
		2	15	2150										
		3	16	1900										
		4	21	1500										
		5	24	1200										
2	-	1	15	3000	8	6	1	14	220	14	4	1	9	3000
		2	18	2400										
		3	20	1800										
		4	23	1500										
		5	25	1000										
3	-	1	15	4500	9	6	2	18	240	15	12	1	12	4500
		2	22	4000										
		3	33	3200										
4	-	1	12	45000	10	2	1	15	450	17	11	1	14	4000
		2	16	35000										
		3	20	30000										
5	1	1	22	20000	11	7	1	12	450	16	13	1	20	3000
		2	24	17500										
		3	28	15000										
		4	30	10000										
6	1	1	14	40000	12	5	1	22	2000	18	16	1	9	3000
		2	18	32000										
		3	24	18000										

Fig. 4: Configuration of Zheng network activities

Table 3: Time, Cost, Number of execute options and Prerequisites of activities of Zheng network.

No	Pr	Op	Ti	Cost	No	Pr	Op	Ti	Cost
1	-	1	14	23000	4	1	1	12	45000
		2	20	18000			2	16	35000
		3	24	12000			3	20	30000
2	1	1	15	3000	5	2	1	22	20000

		2	18	2400		3	2	24	17500
		3	20	1800			3	28	15000
		4	23	1500			4	30	10000
		5	25	1000					
		1	15	4500			1	14	40000
3	1	2	22	4000	6	4	2	18	32000
		3	33	3200			3	24	18000
							1	9	30000
					7	5	2	15	24000
						6	3	18	22000

RESULTS

In order to illustrate the efficiency of our method, it is compared with two of most well-known multi-objective optimization algorithms named as NSGA_II and MOPSO. Parameters for comparison are include: mentioned qualitative measures (GD, S and MS) and the relative average running time of the algorithms (average running time of the algorithms divided on average running time of the SMOCSS algorithm). A random initial population is created for each of the 10 runs on each test problem. All of the algorithms are implemented in Matlab. The results obtained for test problems can be presented as follows:

Test problem 1- ZDT1

The comparison of results between the Pareto fronts produced by NSGA-II, MOPSO and SMOCSS of ZDT1 and the true Pareto front are shown in Fig. 5(a)–(c), respectively.

Fig.5: Pareto fronts produced by (a) NSGA-II, (b) MOPSO and (c) SMOCSS on test function ZDT1.

From the Fig. 5, it can be observed that all algorithms are able to find solutions near the global Pareto front. The values of the three metrics for each algorithm are shown in Table 4. Considering all of the metrics from Table 4, it can be seen that new algorithm (SMOCSS) is the best among the three adopted algorithms.

Table.4: Results for ZDT1: The mean values of the three metrics and relative run time for each algorithm

	NSGA_II	MOPSO	SMOCSS
GD (mean)	0.0149	0.1299	0.0058
S (mean)	0.0030	0.1261	0.0030
MS (mean)	0.9761	0.9879	1
Relative Run Time	5.41	1.35	1

Test problem 2- ZDT3

The comparison of results between the Pareto fronts produced by NSGA-II, MOPSO and SMOCSS of ZDT3 and the true Pareto front are shown in Fig. 6(a)–(c), respectively.

Fig.6: Pareto fronts produced by (a) NSGA-II, (b) MOPSO and (c) SMOCSS on test function ZDT3.

From the Fig.6 it can be revealed that the NSGA_II and the MOPSO algorithms are stuck in a local Pareto optimum, but the SMOCSS algorithm is able to evolve a diverse and well distributed near-optimal Pareto front by spending less run time. The values of the three metrics for each algorithm are shown in Table 5. Considering all of the metrics from Table 53, it can be seen that new algorithm (SMOCSS) is the best among the three adopted algorithms.

Table.5: Results for ZDT3: The mean values of the three metrics and relative run time for each algorithm

	NSGA_II	MOPSO	SMOCSS
GD (mean)	0.4389	0.211	0.0079
S (mean)	0.2917	0.0084	0.0039
MS (mean)	0.6978	0.6713	0.9102
Relative Run Time	4.89	1.13	1

Test problem 3- FON

The comparison of results between the Pareto fronts produced by NSGA-II, MOPSO and SMOCSS of FON and the true Pareto front are shown in Fig. 7(a)–(c), respectively.

Table.6: Results for FON: The mean values of the three metrics and relative run time for each algorithm

	NSGA_II	MOPSO	SMOCSS
GD (mean)	0.0016	0.0006	0.008
S (mean)	0.0012	0.0004	0.0005
MS (mean)	0.9960	0.9994	0.9991
Relative Run Time	4.53	1.09	1

From the Fig.7 it can be seen that all algorithms are able to evolve a diverse and well distributed near-optimal Pareto front for this problem but the computation time required for NSGA_II and MOPSO algorithms are more than the run time required for SMOCSS algorithm. So that even the NSGA_II run time about 4.5 times more that the same for our algorithm. The values of the three metrics for each algorithm are shown in Table 6. Considering all of the metrics from Table 6, it can be seen that all algorithms are usable to optimizing this problem.

Fig.7: Pareto fronts produced by (a) NSGA-II, (b) MOPSO and (c) SMOCSS on test function FON.

Test problem 4- POL

The comparison of results between the Pareto fronts produced by NSGA-II, MOPSO and SMOCSS of POL and the true Pareto front are shown in Fig. 8(a)–(c), respectively. From the Fig.8 it can be seen that similar to the previous problem, all algorithms are able to evolve an almost diverse and well distributed near-optimal Pareto front for this problem but the computation time required for NSGA_II and MOPSO algorithms are more than the run time required for SMOCSS algorithm. So that even the NSGA_II run time about 4 times more that the same for our algorithm. The values of the three metrics for each algorithm are shown in Table

7. Considering all of the metrics from Table 7, it can be seen that NSGA_II is better than MOPSO but it requires more run time and both of this two algorithms are not as good as SMOCSS.

Fig.8: Pareto fronts produced by (a) NSGA-II, (b) MOPSO and (c) SMOCSS on test function POL.

Table.7: Results for POL: The mean values of the three metrics and relative run time for each algorithm

	NSGA_II	MOPSO	SMOCSS
GD (mean)	0.0493	0.0701	0.0277
S (mean)	0.0210	0.0478	0.0121
MS (mean)	0.9900	0.9908	0.9961
Relative Run Time	4.16	1.01	1

The Feng and the Zheng activities network, mentioned in section 3, were solved by NSGA-II, MOPSO, MAWA-CSS and SMOCSS algorithms and the results were compared in the number of non-dominated solutions and relative run time of algorithms. All of the algorithms are implemented in Matlab and each problem was solved 10 times and mean of results was recorded. Table 8 shows the number of non-dominated solutions and relative run time of algorithms.

Table 8: The number of non-dominated solutions and relative run time of algorithms.

Network	the number of non-dominated solutions				Run Time Run Time of the SMOCSS			
	NSGA-II	MOPSO	MAWA-CSS	SMOCSS	NSGA-II	MOPSO	MAWA-CSS	SMOCSS
Feng	44	44	44	44	2.2	2.1	1.1	1
Zheng	23	23	23	23	2.8	1.9	1.2	1

It can be seen from table 8 that SMOCSS algorithm is faster than other algorithms and also is able to find all solutions in pareto set and MAWA-CSS is not as good as SMOCSS algorithm but is faster than MOPSO and NSGA-II. Furthermore, sometimes the MOPSO and the NSGA-II could not find all solutions of Feng

activities network.

As a result of solving the Zheng and Feng activities networks with SMOCSS Following solutions achieved (table 9 and table 10).

Table 9: Results of solving the Zheng activities networks with SMOCSS

Time	Cost	Time	Cost	Time	Cost	Time	Cost
60	143500	67	123500	78	107500	92	98300
61	142500	68	118500	81	106900	94	97800
62	140000	71	117900	83	105500	95	97500
63	131000	73	117300	84	101500	97	97000
65	130400	74	112500	87	99500	105	96200
66	128500	77	110500	90	98900		

Table 10: Results of solving the Feng activities networks with SMOCSS

Time	Cost	Time	Cost	Time	Cost	Time	Cost
100	133320	111	106020	125	102820	142	100870
101	128320	112	105770	126	102570	143	100770
102	128070	114	105270	128	102320	145	100570
103	127820	115	105020	131	102170	148	100270
104	120320	116	104770	132	101970	151	100070
105	120070	118	104470	133	101820	154	100010
106	119820	119	104220	134	101570	156	99950
107	119770	120	103970	137	101510	158	99900
108	119270	121	103820	138	101470	159	99870
109	119020	122	103570	139	101170	161	99820
110	106270	124	103070	140	100970	169	99740

Fig. 9 and Fig. 10 shows all results of solving the Zheng and Feng activities networks by SMOCSS respectively.

Fig.9: All results of solving the Zheng activities networks by SMOCSS.

Fig.10: All results of solving the Feng activities networks by SMOCSS.

CONCLUSION

In this paper, a new multi-objective optimization algorithm, named as SMOCSS, is proposed. The proposed algorithm is based on the recently developed algorithm, charge system search (CSS). In this approach, each particle creates an electrical field around itself and consequently affects other particles by a force which is a result of this attraction field. By this pattern, better particles attract worse particles. The overall structure of this new algorithm is similar to the MOPSO and to determine the Charge magnitude of particles a new simple method is introduced. A comparative study of SMOCSS and two state-of-the-art MO algorithms on four benchmark test problems is presented. The results of applying three performance metrics clearly indicate that SMOCSS is competitive and even outperforms most of the selected MO algorithms. The comparison of the computational time shows that SMOCSS requires less computer time than the selected MO algorithms on some of the selected benchmark test problems.

Construction time-cost trade-off problems are large scale two-objective optimization problems and finding out all solutions in Pareto set with spending reasonable time is very important. By generalizing the well-known Charged Search System (CSS), with using of a new method (SMOCSS), to optimize multi-objective problems, not only the optimal solution could be found in reasonable time, but also the Pareto front could be defined that will provide more effective information and basis for further and correct decision-making. The result of proposed model is compared with MAWA-CSS algorithm, as another multi-objective optimizer, and also NSGA-II and it is concluded that current procedure of modeling TCTP has several advantages especially in terms of generating better solutions and consuming less time for solving the problem.

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