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A CHAOS WITH DISCRETE MULTI-OBJECTIVE PARTICLE SWARM OPTIMIZATION FOR PAVEMENT MAINTENANCE

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ABSTRACT

Particle Swarm Optimization (PSO) is a very popular technique in swarm intelligence. PSO has been applied to solve many problems that have single or multi-objectives. In fact, the multi-objectives optimization problems in real life are combinatorial in nature. Therefore, PSO has been developed to be able to handle large number of decision variables and reduce computational complexity. In this paper, a chaos multi objective PSO algorithm is developed for solving discrete (binary) optimization problems. The developed algorithm is applied to pavement management problem to find optimal maintenance and rehabilitation plan for flexible pavement with maximum pavement conditions and minimum maintenance cost. The results show that there is significant improvement in the solutions satisfying pavement conditions and maintenance cost objectives. It is required to a very short time of execution by the developed algorithm to reach a very good solution. In addition, it is found that it is able to converge to the solution faster than another PSO algorithm.

Keywords: *Multi-Objective Optimization, Pavement Maintenance, Particle Swarm Optimization, Chaotic Mapping, Binary PSO.*

1. INTRODUCTION

Pavement Management System (PMS) works to maintain all pavement sections at a sufficiently high level of service and structural conditions. PMS for roads requires use of resources and a reasonable low budget in order to provide safe ways for users. The functional and structural conditions of pavement are usually deteriorating with time due to various factors such as changing temperatures, heavier loads, repeated adverse weather conditions, these factors may be lead to texture loss, potholes and cracking**.** Therefore, early maintenance is necessary to reduce the cost of maintenance and rehabilitation.

There are several researchers use various computational intelligence methods for pavement maintenance decision. Fwa et al. [4] proposed a single-objective optimization model based on genetic algorithm called "PAVENET" to analyze the pavement maintenance programming problems at the network level. PAVENET was used to examine the effects of resource parameters, network parameters and maintenance-policy parameters. Herabat and Tangphaisankun [16] developed a single and multi-objective optimization model using genetic algorithm to enhance the decision-making procedure of the pavement management in Thailand and to identify the feasible multi-year intervention programs. Moreira et al. [14] developed a two level procedure to solve pavement optimization problem with three objectives: maintenance costs, user costs, and pavement condition. Genetic algorithms were used to solve those multi-objective optimization problems. Terzi and Serin [23] introduced a single objective ant colony for pavement management system at the network level. The single objective function, maximization of the work of pavement intervention, was adopted for scheduling routine intervention activities. Shen et al. [20] implemented Chaos Particle Swarm Optimization (CPSO) on a single objective continuous optimization problem to find optimal pavement maintenance decision for expressway. Mahmood [12] introduced a novel barebones Particle Swarm Optimization (PSO) to solve a discrete optimization problems. This algorithm was used for flexible pavement in order to find optimal maintenance decisions. Many previous studies have relied on the use of single objective PSO for finding pavement maintenance plan, so there is a need for a multi objectives PSO as many problems have more than one objective. The primary aim of this research is to develop the PSO algorithm and apply it to find optimal maintenance and rehabilitation plan for flexible pavement to satisfy the two objectives (minimization of the treatment cost and minimization of the sum of all residual Pavement Condition Index (PCI) values).

2. PAVEMENT MAINTENANCE DECISION PROBLEM

2.1 Problem Parameters

There are data and decision criteria used to perform maintenance and rehabilitation analysis. Those data and decision criteria are existing condition of the pavement based on distresses, minimum acceptable level of service, study period, maintenance cost and the budget. To estimate the maintenance needs, the highway network is divided into a number of pavement sections which have equal length [5].

Agency cost of highway network is the intervention required to design, build and invest a highway network. It comprises of the cost of maintenance, rehabilitation and reconstruction. Rehabilitation is required for highway network at least once in its lifetime to maintain it above the minimum acceptable service and safety level. If a rehabilitation activity is to be implemented in subsequent years, then its cost can be deducted to the present value as the following [12]:

$$\text{Present cost} = \text{Future cost} \times \text{PWF} \quad (1)$$

Where, PWF is the Present Worth Factor, given by:

$$PWF = \frac{1}{(1+DR)^t} \quad (2)$$

The typical range of discount rates *DR* recommended by Federal Highway Administration (FHWA) is 3 to 5% [6]

t = time at which the money is spent (specified in years).

Depending on the condition, highway authorities have the option to select rehabilitation action from an activities list of. Such list, which is also adopted in this research, is shown in table 1. Furthermore, it is necessary to determine the trigger level for each maintenance activity. The trigger level is defined as the minimum level of pavement service ability, such that the maintenance must be implemented when the pavement section reaches it. The highway authority usually specifies the total length of the study period. Moreover, the length of the unit analysis period, that are commonly one year, is chosen based on the requirements of the highway agency [13].

2.2 Objective Functions

Pavement maintenance systems have common objectives as defined by road authorities include: To minimize user costs by selecting and scheduling treatment procedures, to minimize the treatment costs over the analysis period, and maintaining the pavement performance over the minimum acceptable level with resources available[5]. To make optimal investment decisions in the maintenance field, it is important to improve the M&R decision in view of multiple objectives such as maximum performance, minimum cost, etc. Therefore, the particle swarm optimization technique with multi-objective is used for scheduling pavement maintenance activities. Multi-objective programming for pavement maintenance and rehabilitation can be formulated mathematically as follows [12]:

Minimize the total pavement maintenance cost

$$f_1(x) = \sum_{d=1}^{D} \sum_{p=1}^{N} \sum_{m+1}^{M} x_{m,p,d}\ C_m\, L_p\, W_p\ (1+DR)^{-d} \quad (3)$$

minimize the sum of all residual PCI values

$$f_2(x) = \sum_{d=1}^{D} \sum_{p=1}^{N} \sum_{m+1}^{M} x_{m,p,d}\ \left[\left(PCI_{max} - PCI_{p,d}\right) L_i\, W_p\ AADT_{p,d}\right] \quad (4)$$

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Where,

$$x_{m,p,d} = \begin{cases} 1, & \text{if treatment } m \text{ for section } p \text{ at time } d \text{ is selected} \\ 0, & \text{otherwise} \end{cases}$$

where d is any time in the analysis period, and D is the total analysis period (both are usually specified in years); N is the total number of pavement sections; m is the treatment type; M stands for the total number of treatment types; p is the pavement section number under consideration; Lp is the length of pavement section p; Cm is the unit cost of treatment type m; DR is the discount rate; Wp stands for the width of section p; PCImax is the maximum PCI level (100 %); PCIp,d = PCI for section p at time d; AADTp,d is the annual average daily traffic for section p at time d.

2.3 Pavement Condition Prediction Model

The Pavement condition index (PCI) is indicator to evaluate the overall conditions of pavement. It is based on visual survey results that are determined by distress type, quantity, and severity. Field verification of the assessment method has showed that PCI is a decent indicator of structural integrity and also to determine both the current state and future serviceability under current traffic conditions. A pavement deterioration model is an vital stage when estimating treatment needs, and when determining road user costs and benefits of the treatment application[19]. Therefore, there is essential to prediction models that capable to estimate pavement deterioration by considering distress, traffic loading, pavement age, and maintenance effects. For arterial roads in the wet freeze climatic region is adopted to estimate future pavement condition:

$$\mathrm{PCI} = 97.744 - 0.15\,\mathrm{X5} - 0.064\,\mathrm{X4} - 0.515\,\mathrm{X2} + 3.748\,\mathrm{X3} \qquad (5)$$

Where *PCI* = pavement condition index*; X5* = cracking area (alligator, edge, and block); *X2* = pavement age; *X3* = maintenance effect (inlay and overlay thickness); *X4* = longitudinal and transverse cracking length [12].

3. PARTICLE SWARM OPTIMIZATION

PSO is a swarm intelligence optimization algorithm suggested by Kennedy and Eberhart [7]. PSO is based on the simulation of birds' behavior. The advantages of the algorithm are: few adjustable parameters, simple principle and the fast convergence speed. Therefore, PSO has been widely used in many fields [11]. Each possible solution in search space represents by particle. During each iteration, the particle updates his velocity and position according to the following equations:

$$V_{i,j}(t+1) = \mathrm{w}\, V_{i,j}(t) + r_1 c_1 \left[Pbest_{i,j}(t) - X_{i,j}(t)\right] + r_2 c_2 \left[Gbest(t) - X_{i,j}(t)\right] \qquad (6)$$

$$X_{i,j}(t+1) = X_{i,j}(t) + V_{i,j}(t+1) \qquad (7)$$

Where $X_{i,j}(t)$ is a position of particle $\boldsymbol{i}$ at iteration $\boldsymbol{t}$ and it depends on previous position and previous velocity; $V_{i,j}(t)$ is a velocity of particle $\boldsymbol{i}$ at iteration $\boldsymbol{t}$; $\boldsymbol{c_1}$ and $\boldsymbol{c_2}$ are learning factors that are fixed numbers; $\boldsymbol{r_1}$ and $\boldsymbol{r_2}$ are two random number between (0,1); $\boldsymbol{w}$ is the inertia weight that is used to control the influence of the previous velocities on the current velocity [2]; $Pbest_{i,j}(t)$ is the local best position for *j*th dimension of particle $\boldsymbol{i}$ that have the smallest fitness value obtained so far at iteration $\boldsymbol{t}$; Gbest(t) is the particle leader or global best position at iteration $\boldsymbol{t}$, which is guides the particles to move towards the optimal positions.

The performance of each particle in the swarm is assessed according to fitness function of the optimization problem [22][17].

4. MULTI-OBJECTIVE OPTIMIZATION PROBLEMS

In multi objective scenario, solutions are compared against different objectives. Therefore, there is no single dominated solution but there are a set of non-dominated solutions called Pareto-optimal solutions. Pareto optimality means that none of the objective can be improved without making a negative effect on at least one of the other objectives[14]. The storage known as the archive is used to store the solutions obtained during the generations and thus used to select the leader of the swarm according to some sort of quality measures [1]. In this paper, the sigma method is used to find the particle leader [15].

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5. DISCRETE PARTICLE SWARM OPTIMIZATION

In 1997, Kennedy and Eberhart proposed a discrete version of PSO algorithm for solving discrete problems[8]. The most popular type of discrete PSO is a binary algorithm. In binary PSO, the position of each particle will be 0 or 1 [18]. The position will update according to the following equations[9][24]:

$$V_{i,j}(\mathrm{t}) = sig\left(V_{i,j}(\mathrm{t})\right) \qquad (8)$$

$$sig\left(V_{i,j}\right) = \frac{1}{1+e^{-Vi,j(t)}} \qquad (9)$$

Where sig is the sigmoid function and $V_{i,j}(\mathrm{t})$ is the velocity of each particle in each iteration.

The position equation is changed to make the positions of all particles is either 0 or 1 according to the following equation:

$$X_{i,j}(\mathrm{t}+1) = \begin{cases} 1 & if\ rand < sig\left(V_{i,j}(\mathrm{t}+1)\right) \\ 0 & otherwise \end{cases} \qquad (10)$$

Where $rand$ is a quasi-random number between (0, 1).

6. CHAOTIC SEQUENCES FOR INITIAL POPULATION

Chaos is a nonlinear phenomenon which is widely found in nature. chaos is easy of implementation and also has a special ability to avoid trapped in local optima[3]. In original PSO algorithm, randomization is used to initial the population (position and velocity). In this research, the chaos map is employed to initialize the population instead of randomness to improve the diversity without changing the algorithm randomness when the population is initialized. In addition, the logistic map is used because it considers one of the most popular kind of chaotic sequences. The logistic map equation is defined as following:

$$Z_{n+1} = \mu\, Z_n(1 - Z_n) \qquad n = 1,2,3 \ldots\ldots \qquad (11)$$

Where μ is the control parameter = 4; Z_1, Z_2, Z_3…. Z_n are chaotic series used to initialize the population of PSO[21].

7. CHAOTIC WITH PARTICLE SWARM OPTIMIZATION FOR DISCRETE PROBLEM

To achieve our hypothesis, Chaotic with Discrete Particle Swarm Optimization (CDPSO) is developed and implemented. The following steps are considered to implement the suggested algorithm:

1- Using the chaotic map to initialize a population of 100 particles. The logistic map as in equation (11) is used where the initial value of this equation *z(0)* is equal to 0.7 [26].

2- For discrete problem, the direct (continuous) representation of positions is converted to indirect (binary) representation

3- Before starting the generations, the initialization of local best position is done by assuming to be equal to the initial position of the particle.

4- Evaluate the solutions using the objective function (fitness function). The first one is for PCI value (using equations 4 and 5) and the second one is for cost (using equations 1, 2, 3).

5- Choose the best solutions based on Pareto front as shown in (Multi-Objective Optimization Problems) and save the solutions in the external archive (A).

6- Check whether the archive (A) is full or not. If A is full (in this paper, the archive capacity is determined to store only 20 solutions) then Crowding Distance Computation (CDC) [21][22] is applied to determine the deletion of non-dominated solutions from the archive. The following steps are used:

a- From the archive, obtain the number of non-dominated solutions.

b- Initialize array of distance (D) for all particles (Initialize with zero).

c- Find the solutions which have the highest and lowest fitness values for each objective function. The two objectives *(M)* are always selected because they are given an infinite crowding distance values.

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Set the CDC (1, M) = CDC (end, M) = infinity value.

d- After computing the CDC of each solution, the non-dominated solution using each objective value *M* are sorted in ascending order. Then, for each particle, the distance between the upper and the lower particles from this particle is calculated. The CDC of particle *i* represents the sum of distances of particles (*i-1*) and (*i+1*) divided on the subtraction between the maximum and minimum value of each objective.

e- Sort the array of CDC in descending order. Then 20% of particles which have the highest CDC will be chosen.

7- Choose the particle leader or the global best position. The sigmoid method is employed in this research to choose the leader from the non-dominated solutions. The sigmoid method can be calculated as the following:

$$\sigma = \frac{f_1^2 - f_2^2}{f_1^2 + f_2^1} \qquad (12)$$

f_1, f_2 are fitness values for the first objective function and the second objective function respectively. The procedure of sigmoid method is given by the following:

a- Calculate the $\sigma(j)$ for the members in (A) according to equation (12).

b- Calculate $\sigma(i)$ for each particle using Euclidian distance (Dist) between $\sigma(1)$ and $\sigma(i)$. Then, calculate Euclidian distance between $\sigma(j)$ and $\sigma(i)$ (tempDist).

c- Compare the (Dist) with all (tempDist), if tempDist ≤ Dist then Dist = tempDist. Otherwise, Dist will not change. The particle that has the lowest (Dist) represent the particle leader [15].

8- Update the velocity of particles according to equation (6). The value of w is decreased linearly from 0.9 to 0.4 according to the following equation:

$$W = W_{max} - \frac{W_{max} - W_{min}}{Tmax}\, T \qquad (13)$$

Where *Tmax* is the maximum number of iterations; *T* is the current iteration [10]; the values of c_1 and c_2 are equal to 2 [12]; and r_1, r_2 are two random numbers between (0,1).

9- Use a controlled mutation to keep the velocity in the range (-6,6) as recommended by Kennedy and Eberhart for discrete problems [7].

10- Update the position of particles using equations (8) (9) (10). Then, mutation operator is applied to avoid falling in local optimal. The mutation is done by changing the positions of number of particles selected randomly.

11- Evaluate the fitness value of the new particles. The new solutions are saved in order to compare it with the previous solution.

12- Update the local best solution using the following equation [25].

$$pbest_i\ (t+1) = \begin{cases} pbest_i\,(t), & if\ F(pbest_i\,(t)) < F(x_i\,(t+1)) \\ x_i\,(t+1), & otherwise \end{cases} \qquad (14)$$

13- Pareto front is used again to choose the best solution. Then the new solutions and their positions are saved in the external archive.

14- After saving the new solutions, the external archive should be checked again as in step 6.

15- Choose a new leader in the current iteration as in step 7.

16- Repeat steps 8 to 15 until the maximum number of iterations is reached. In this research, the maximum iteration is 100.

8. COMPROMISE SOLUTION

To address the subjectivity of decision makers, a fuzzy membership function is adopted to mimic the authority preferences and to identify the compromise solution from the Pareto optimal set. Considering a non-dominated solution Y_k in the archive, the satisfactory degree of Y_k for the ***i***th objective function F_i is expressed by a membership function:

$$\mu_i^k = \begin{cases} 1, & F_i(Y_k) \le F_i^{min} \\ \dfrac{F_i^{max} - F_i\,(Y_k)}{F_i^{max} - F_i^{min}}, & F_i^{min} < F_i(Y_k) < F_i^{max} \\ 0, & F_i(Y_k) \ge F_i^{max} \end{cases} \qquad (15)$$

where F_i^{min} and F_i^{max} are the minimum and maximum of the ***i***th objective function Fi. Then, the normalized membership function μ^k of Y_k is calculated by:

$$\mu^k = \frac{\sum_{i=1}^{M} \mu_i^k}{\sum_{k=1}^{|A|} \sum_{i=1}^{M} \mu_i^k} \qquad (16)$$

Where M is the number of objective, |A| is the element number of the archive. The compromise solution is the one having the maximum of μ^k in the archive A [25].

9. RESULTS

The proposed Chaos with Discrete Multi Objective Particle Swarm Optimization (CDMOPSO) is implemented to find the optimal maintenance plan for five pavement sections over 10 years. The obtained results are shown as in the figure 1. To simulate the agency preferences, the compromise solution which has the maximum membership value (μ) in the archive is selected as the optimal pavement maintenance solution. Table 2 shows the optimal maintenance of compromise solution after 100 generations. The maintenance cost of compromise solution is 199.12 while the sum of all residual PCI values is 3.1118e+09. The execution time is about two minutes, which is very short time to converge to optimal solutions compared with that achieved by DBB-MOPSO algorithm [10] as shown in figure 2. The results show significant improvement in the maintenance cost and pavement performance compared to the results obtained in the previous work that applied for the same problem [7] (399.25 for maintenance cost and 5.87E+10 for sum of all residual PCI values). This means that the use of chaotic map instead of randomization to create a population has increased the diversity of the population and thus has been increase the search space and find more suitable solutions. In addition, initialization of the position with chaotic map had an impact on the *Pbest* values, because the set of *Pbest* is equal to the set of position (initialize the *Pbest* before starting of generations). The convergence of the developed algorithm to optimum solution could be achieved after 50 generations. Figures (3 to 6) show the convergence pattern with number of generations. Table 3 shows the solutions that obtained in 100 generations with CDMOPSO.

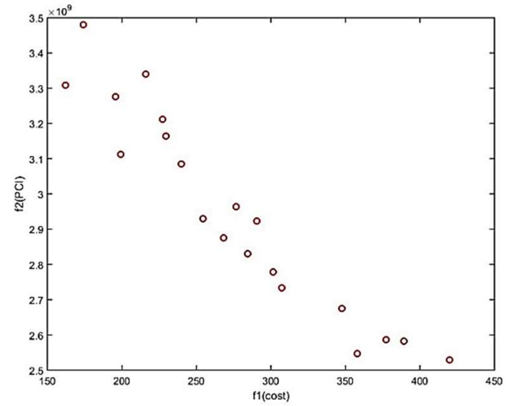

Figure 1. The Non-Dominated Solutions after 100 Generations.

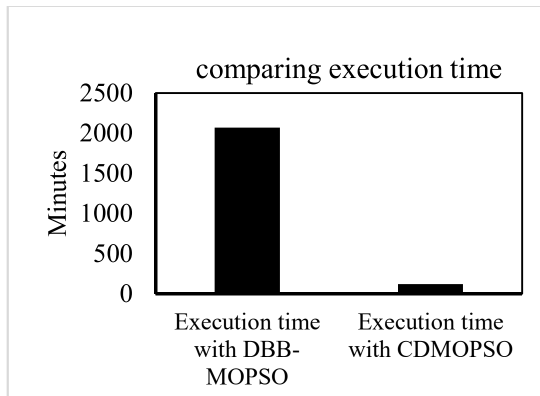

Figure 2. The Execution Time of Two Algorithms.

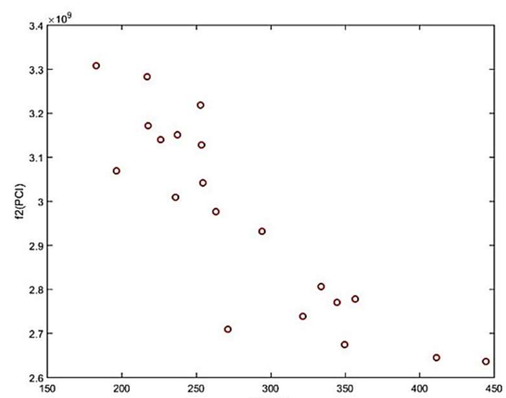

Figure 3. The Non-Dominated Solutions at 20 Generations.

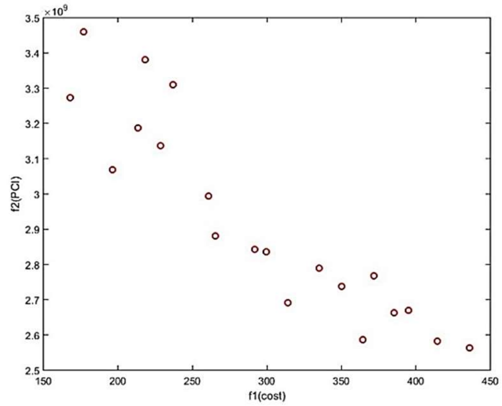

Figure 4. The Non-Dominated Solutions at 40 Generations.

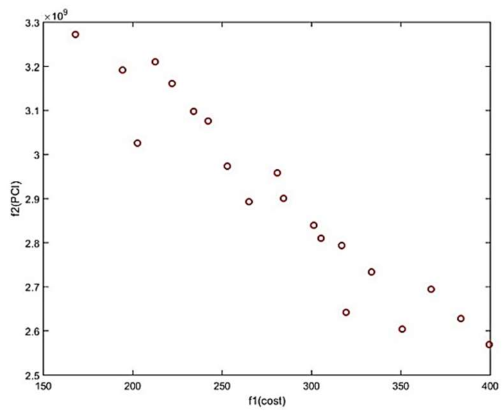

Figure 5. The Non-Dominated Solutions at 60 Generations.

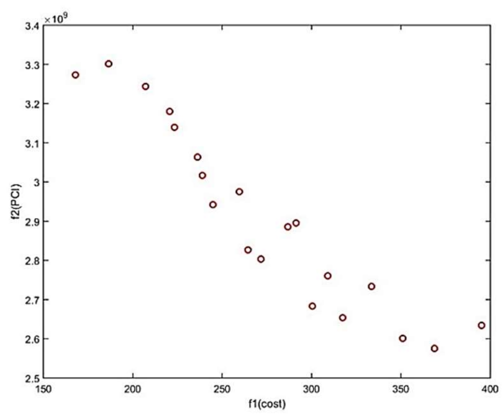

Figure 6. The Non-Dominated Solutions at 80 Generations.

10. CONCLUSIONS AND FUTURE WORKS

The proposed algorithm is implemented to find the best pavement maintenance and rehabilitation scheduling considering two objectives: the minimization of the sum of all residual PCI values and the minimization of the total pavement rehabilitation cost. The execution-time of the developed algorithm to reach an optimal solution is too short.

Using the ergodicity characteristics of chaotic variables instead of randomness values to the initialization of population makes a better diversity in population. This is further improvement in the performance of the developed algorithm.

In future, different evolutionary algorithms can be applied to conduct additional testing of the developed algorithm performance. As this study is only focused on an unconstrained optimization problem, the CDMOPSO algorithm can be implemented on constrained problems as future work to examine the effects of using another chaos types on the solutions and the execution time.

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Table 1. Pavement Maintenance and Rehabilitation Strategies.

No	M&R strategy
1	Do nothing
2	AC* overlay 1in(25mm)
3	AC* overlay 2in(50mm)
4	AC* overlay 4in(100mm)
5	AC* overlay 6in(150mm)

(*Asphalt Concrete)

Table 2. Optimal Maintenance of Compromise Solution.

Year 1					Year 2					Year 3					Year 4					Year 5					Year 6					Year 7					Year 8					Year 9					Year 10				
1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5
0	1	0	0	1	1	0	0	0	0	0	1	0	0	0	0	1	0	0	1	0	0	0	0	0	1	0	0	0	1	1	0	1	1	0	1	0	1	0	0	0	1	0	1	0	1	0	1	0	0
0	0	1	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	1	0	0	1	1	0	0	0	1	0	0	1	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	1
1	0	0	1	0	0	0	0	0	1	0	0	0	1	1	1	0	1	1	0	0	1	1	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	1	0	0	0	0	0	0	0
0	0	0	0	0	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	1	0	0	0	1	0	0	0	0	0	1	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	1	0	1	0

Table 3. The Non-Dominated Solutions with CDMOPSO.

Solution in 100 Generations	
Cost	Sum of PCI
162.15	3.3083e+09
419.97	2.5299e+09
216.13	3.3403e+09
239.88	3.0856e+09
276.53	2.9643e+09
377.15	2.5859e+09
389.25	2.5824e+09
195.77	3.2756e+09
347.58	2.6753e+09
199.12	3.1118e+09
357.92	2.5468e+09
268.17	2.8752e+09
301.31	2.7781e+09
174.09	3.4797e+09
229.58	3.1638e+09
290.56	2.9237e+09
307.2	2.7341e+09
254.49	2.9304e+09
227.1	3.2117e+09
284.4	2.8308e+09