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Multi-objective Waste Load Allocation in River System by MOPSO Algorithm

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ABSTRACT: This paper explores the capabilities of Multi-objective Particle Swarm Optimization algorithm in a simulation-optimization model for solving waste load allocation problems. The main goals are total treatment costs, violation of the water quality standards and equity. In this research, the water quality simulation model is coupled with a multi-objective optimization model, MOPSO. In order to derive non-dominated solutions, two different optimization models are used. The first is referred to as the cost versus quality model and the second one also consider minimizing cost and inequity. For the each case, the trade-off curve (Pareto front) is derived and the best non-dominated solution on the trade-off could be selected by stakeholders and decision makers. The proposed model has been developed for Haraz River in the northern part of Iran which represented scenarios considering different interests and answered questions to modify scenarios according to the decision makers' ideas. Solutions were compared with NSGA-II, and the results demonstrate a suitable convergence and diversity of proposed algorithm.

Key words: Waste Load Allocation, Equity, MOPSO, Multi-objective optimization

INTRODUCTION

Due to rapid population growth, strong dependence of living organisms on water, progressive reduction in available healthy water resources, and excess wastewater, the planning and monitoring of water must be performed more accurately and rapidly. Rivers are one of available water resources that should find a solution for their waste discharges. In general, the problem of surface water quality is related to the development plans in the basins so that stakeholders' discharge to the rivers without appropriate treatment. For better water quality management and more sustainable decision making, one should determine the treatment levels regarding to the environment, economic and social aspects under waste load allocation policy.

Waste Load Allocation (WLA) refers to the determination of the required pollutant removal (or treatment level) at different point sources to ensure that water body standards are maintained throughout the receiving water body. Optimal waste load allocation implies that the treatment vector selected not only maintains the water quality standards, but also results in the best value for the objective function defined for the management problem (Burn and Lence 1992). The waste load allocation can satisfy quality standards in the system and simultaneously minimize the costs imposed to the treatment facilities. Therefore, it requires multi objective optimization models to find the best solution. However, in surface water quality management, water distribution network, reservoir operation and waste load allocation, the utilization of simulation-optimization techniques can provide more efficient plans with expanded capability.(Burn and Yulianti 2001, Eusuff and Lansey 2003, Rani and Moreira 2010).

The waste load allocation models are presented as multi-objective models considering the criteria of different stakeholders that may contradict each other, for example, maximizing economic efficiency and measures of water quality by checking the violation from the standard of dissolved oxygen. moreover, minimizing of the total treatment cost and also increasing equity among the polluters, subject to limitations on satisfaction of DO standard at all of the check points along river.(Mujumdar and Subbarao Vemula 2004, Yandamuri, Srinivasan *et al*. 2006). Metaheuristic algorithms are among efficient tools for solving optimization problems that can find the optimum solution in multi objective problems. There are several means for solving multi-objective optimization problems, such as genetic algorithms,

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simulated annealing, tabu search, ant colony, and others, the genetic algorithms method is most commonly used to solve waste load allocation problems. (Yandamuri, Srinivasan *et al*. 2006, Saadatpour and Afshar 2007, de Andrade, Mauri *et al*. 2012). Some previous works were done in this field, Sasikumar and Mujumdar (1998), proposed a two-objective fuzzy optimization model in waste load allocation and called it maximum-minimum model. Chang, Chen *et al*. (1997), solved the waste load problem in the river by combining fuzzy optimization with genetic algorithm. Mujumdar and Sasikumar (2002), solved the maximum-minimum model by combining fuzzy risk in seasonal conditional rivers. In the form of three two-objective models,Burn and Yulianti (2001), attempted to model the waste load allocation problem using genetic algorithm.

Two models were for the design phase and one model to the operational phase. Using the simulator model QUAL2K and the genetic algorithm, Saadatpour and Afshar (2007), addressed the waste load allocation in uncertain conditions. In their research, the cost function and the quality standards for water were considered to be fuzzy values. Yandamuri, Srinivasan *et al*. (2006), solved the waste load allocation problem in the form of two multi-objective models using genetic algorithm. In the first model (cost-performance), only the minimization of violations of quality standard was considered but in the second model (cost-equity-performance), the equity index was also included, Mostafavi and Afshar (2011) optimized the cost-performance model by including several different wastes.

This study examined the effectiveness of Multi-Objective Particle Swarm Optimization (MOPSO) algorithm for solving the waste load allocation problem where the objectives include minimizing the treatment cost, violation of the standard and equity. The Streeter-Phelps (S-P) equation model was used to simulate the model (Streeter and Phelps 1958), and the water quality index for Haraz River was the dissolved oxygen in water at control points. Moreover, no report was found of MOPSO algorithm to solve WLA problems. MOPSO was chosen to solve the waste-load allocation problem because it is easy to implement, easy to use and its efficiency has been empirically proven in some previous studies in different areas.(Coello, Pulido *et al*. 2004, Goudos and Sahalos 2006, Durillo, García-Nieto *et al*. 2009, Nikoo, Kerachian *et al*. 2012)

MATERIALS & METHODS

In fact, the optimization problem was to find a solution or solutions on a set of feasible alternatives (respecting the problem constraints) with an aim to optimize the problem objective. On the other hand, problems in water resources management often have a high number of decision variables and the optimization of nonlinear objective functions sometimes are in conflict with each other. Therefore, a set of solutions is obtained. The idea of Multi-objective optimization problem is to find a set of Pareto (non-recessive) solutions to the problem. Baltar and Fontane (2008), used MOPSO to solve a Multi-objective problem and examined its application in three aspects: solving the test functions for comparison with other versions of MOPSO and other algorithms, the multipurpose reservoir operation problem with four objective functions and also the quality operation of reservoir due to thermal bedding with three objective functions.Azadnia and Zahraie (2010) used the MOPSO optimization algorithm for the operation of Sefidrud reservoir. The objectives of this study were to supply downstream needs and sediment discharge. The study also discussed the need for finding non-inferior solutions with high diversity and finding the general optimum appropriate for particle swarm in the MOPSO algorithm, (Rahimi, Qaderi *et al*. 2013), compared the performance of the MOPSO algorithm and the NSGA-II algorithm in the reservoir operation of Doroudzan Dam. The comparison between the MOPSO algorithm results and the NSGA-II multi-objective genetic algorithm showed the efficiency of the former in achieving optimum solutions for the policy of optimum operation for reservoirs in most months of operation. The proposed model has been developed for waste load allocation in Haraz River located in the northern part of Iran. There are eight main dischargers on this river.

The PSO algorithm was first proposed by Eberhart and Kennedy in 1995. The PSO Like all other evolutionary algorithms, begins by creating a random population of individuals called a group of particles. Each particle in the group is a set of different unknown parameters whose optimum values must be determined. In fact, each particle is a point in the solution space. The algorithm essence is to search the solution space based on the movement of the particle group towards the best position faced in the past, hoping to achieve a better position. The difference between the PSO and other evolutionary algorithms is in the method in which the created population moves in the search space. In the PSO, each population member has an adaptive velocity that moves in the search space proportionate with it. In addition, each of them has a memory. That is, they memorize the best position they achieve in the search space. Thus, each member moves in two directions:

1. Towards the best position they are in.

2. Towards the best position the best member is in. In other words, each particle in the PSO represents a feasible solution randomly moving in the problem space.

Thus, the velocity equation for each particle and its new position were defined as follows (Reyes-Sierra and Coello 2006):

$$V_i^{t+1} = wV_i^t + \underbrace{c_1 rand\,(0,1)}_{\varphi_1}(pbest_i - X_i^t) + \underbrace{c_2 rand\,(0,1)}_{\varphi_2}(gbest_t - X_i^t) \quad (1)$$

$$X_i^{t+1} = X_i^t + V_i^{t+1} \quad (2)$$

Where,

V_i^{t+1}: Velocity of particle i at the new iteration

V_i^t: Particle velocity at the current iteration

X_i^t: Particle position in the new iteration

$pbest_i$: The best position that particle i has ever observed

$gbest_t$: The best position of the best particle (the best position that all particles ever observed)

In the search space, each particle changes according to the experience and knowledge of itself and its neighbors. Hence, the position of other particles in the group affects particle search. The result of modeling this social behavior is a search process in which particles tend towards appropriate areas. Particles in the group learn from each other and go towards their best neighbors based on the knowledge gained (Eberhart and Kennedy 1995). & (Coello 1999).

Different criteria are used for solving the waste load allocation problem. Choosing among these criteria depends on their importance from the viewpoint of decision-making authority (Burn and Yulianti 2001). Among these criteria, one can point to minimum percent of treatment or in other words minimizing the total cost, minimum violation of the standards value, equity index or uniform treatment, minimization of maximum violation, maximum capacity in qualitative excess(Niksokhan, Kerachian *et al*. 2009). In this study, the minimum treatment cost criterion, minimum violation of dissolved oxygen from the standard and equity index. The treatment-violation cost criteria and treatment-equity cost criteria were considered as objective functions, and the optimum solutions are achieved for this two-objective problem.

The first model was the minimum cost per treatment per waste production unit for a violation of the minimum set standard. This model shows different values of the optimum cost versus violation values from the standard value. Based on the obtained optimum solutions, the decision maker can select one of the obtained solutions according to constraints. In this case, the problem constraints were the violation values calculated by the S-P equation. The model relations are as follows (Burn and Yulianti 2001):

$$Min \sum_{i=1}^{NS} C_i(x_i) \quad (3)$$

$$Min \sum_{j=1}^{NR} V_j \quad (4)$$

$$S.t$$

$$x_i \in xs_i \qquad \forall i \quad (5)$$

$$V_j = f\,(x, W, Q, T, K, WQ_{std}) \quad (6)$$

Where, C_i is treatment costs for waste source i, x_i is removal percent of waste i, xs_i is a set of selective removal percentages, *Ns* is the number of point sources, V_j is the difference between qualitative parameter value and the standard value at control point j, *NR* is the number of control points, f is the definition of quality conditions, a function of hydraulic conditions and loading in the river, W is waste load of discharger, Q is discharge of the river mainstream and its branches, T is water temperature, K is response coefficient of the system and WQ_{std} is the qualitative standard value in the river system. Moreover, to determine the violation value from the qualitative standard:

$$V_j = \begin{cases} V_j & V_j \geq 0 \\ 0 & V_j \leq 0 \end{cases} \quad (7)$$

Each discharger will bear a certain treatment cost based on their circumstances, for every degree of waste removal. Therefore, the treatment cost function for each discharger treatment can be calculated for any treatment percent and therefore the total treatment cost for units is achieved. To estimate the cost function of dischargers in Haraz River with the system of designed lagoons, data for costs of construction and operation of aerated lagoons in some provinces of Iran and in different counties were collected and analyzed. Cost functions for discharger are estimated as follows:

$$C_i = a_i x^3 + b_i x^2 + c_i x + d_i \quad (8)$$

Where a, b, c, d are given in Table 1.

The above model enters into the MOPSO optimization algorithm, and among possible modes of treatment for each source, dominant solutions are selected. These solutions are obtained as the

Table 1. Cost Coefficient of dischargers

discharger	Cost Function Coefficient			
	a	b	c	d
1	1.13	-0.80	0.16	0.03
2	4.06	-3.25	0.65	0.12
3	1.71	-1.20	0.25	0.04
4	2.01	-1.40	0.28	0.05
5	1.52	-1.07	0.22	0.04
6	1.23	-0.86	0.17	0.03
7	1.87	-1.32	0.26	0.05
8	0.45	-0.32	0.06	0.01

treatment percentage allocated to each source versus the qualitative response of river in each control point using the S-P equations. In the second model, in addition to reducing treatment costs, the inequity index was also studied. The model is as follows (Burn and Yulianti 2001)

$$Min\sum_{i=1}^{NS} C_i(x_i) \tag{9}$$

$$MinEQ \tag{10}$$

$S.t$

$$EQ=\sum_{i=1}^{NS}\left|\frac{x_i}{\overline{x}}-\frac{W_i}{\overline{W}}\right| \quad \forall i \tag{11}$$

$$V_j \le 0 \qquad \forall i \tag{12}$$

$$x_i \in xs_i \qquad \forall i \tag{13}$$

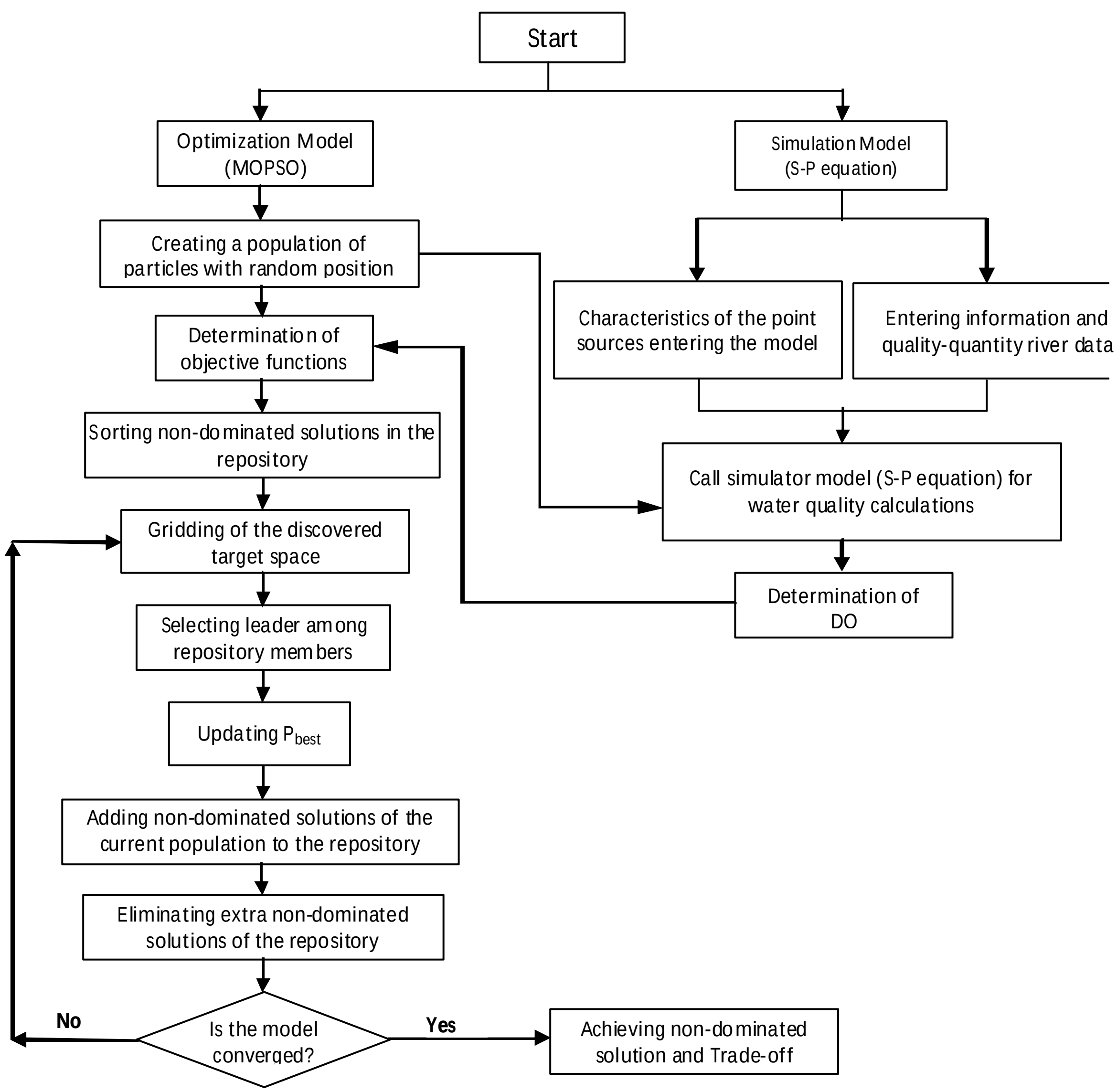

Fig. 1. Optimal waste load allocation framework

Table 2. Characteristics of point sources of Haraz River

Point sources	1	2	3	4	5	6	7	8
distance from upstream (m)	996	10100	11493	14595	15135	22160	25957	38643
Discharge (m^3/s)	0.75	3.251	0.86	1.04	1.616	0.65	0.72	0.302
Dissolved oxygen (mg/l)	5.5	5.8	5.4	5.7	7	5.5	4.6	6.3
BOD (mg/l)	3.2	3	4.2	4.1	2	4	5.5	3
Temperature (°C)	10	11	11	12	12	11	13	13

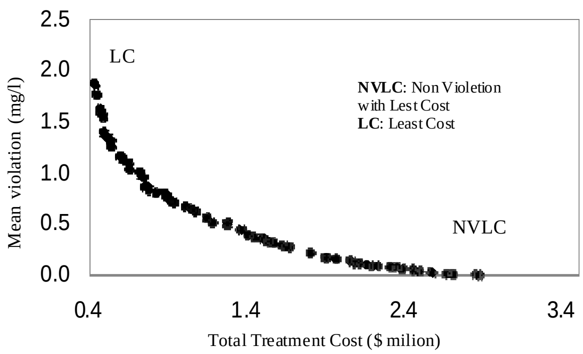

Fig. 2. Cost-violation trade off

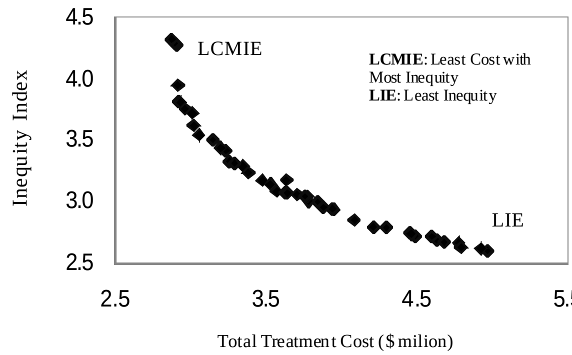

Fig. 3. Cost- Inequity trade off

Table 3. Trade-off curve characteristics

Trade off	Index	Pareto solution	Removal Fraction of each Discharger							
			1	2	3	4	5	6	7	8
Cost-Violation	LC	(0.43 , 1.86)	0.43	0.42	0.44	0.43	0.33	0.4	0.4	0.47
	NVLC	(2.87 , 0.00)	0.93	0.37	0.8	0.86	0.98	0.85	0.76	0.31
Cost-InEquity	LCMIE	(2.88 – 4.32)	0.93	0.37	0.8	0.86	0.98	0.85	0.76	0.31
	LIE	(4.97 - 2.61)	0.73	0.98	0.85	0.93	0.9	0.9	0.98	0.22

Table 4. Waste load allocation scenarios

Scenario	1		2		3		4	
Inequity Index	4		3.5		3		2.6	
Discharger	Cost (M$)	Waste load (kg/d)	Cost (M$)	Waste load (kg/d)	Cost (M$)	Waste load (kg/d)	Cost (M$)	Waste load (kg/d)
1	0.17	51.8	0.28	30	0.22	43.7	0.36	28.6
2	0.64	308.4	1.3	164.7	1.7	90.9	2.1	39.3
3	0.55	23.1	0.75	26.6	0.5	29	0.55	34.8
4	0.57	45.3	0.55	20	0.7	15.9	0.69	4.8
5	0.41	31.1	0.35	36.1	0.35	36	0.27	61.2
6	0.35	27.3	0.13	54.2	0.2	57.4	0.26	67.4
7	0.32	44.9	0.32	67.5	0.45	42.9	0.68	22.4
8	0.02	59.1	0.02	55.6	0.02	59.6	0.02	63.5

$$V_j = f\,(x, W, Q, T, K, WQ_{std}) \quad \forall i \qquad (14)$$

Where, x is mean percentage of treatment, W is mean waste load discharged from the NS waste source, W_i is load of wastes discharged from source i. Other parameters have already been introduced. Equation (11) indicates that discharger with high volume of waste must do more removal. Equation (12) makes violation of the system impossible. The model results indicate that high inequity index is associated with lower costs in the system. Thus, the decision maker must select the appropriate option based on available considerations. In equation (11), the closer the treatment value in a source to the mean treatment and the closer the waste value discharged by a source to the mean value, the equity index value will be lower. The proposed optimal waste load allocation model framework is shown in Fig. 1. It consists of the multi-objective optimization model, with the water quality simulation model embedded into it. This framework can champion both optimization models which specified in this study.

Eight dischargers in selected reach of Haraz River were identified as waste sources and entered into the model. Next, data about point sources entered into the model are given in Tables 2 (Pejman *et al*. 2009).

RESULTS & DISCUSSION

The first model for treatment cost-violation of the standard value ranges from the minimum treatment value per unit for low costs to a treatment value that no violation is observed. If the minimum treatment value is possible, maximum violation of the dissolved standard oxygen will happen. On the other hand, high costs must be paid so that there is no violation of the standard dissolved oxygen. In this model, the decision maker makes decision based on the cost he will spend and the violation of its corresponding standard. In fact, each point in the treatment cost-violation solution curve would be a solution for the decision maker which is showed in Fig. 1. In the second model, for the treatment cost for discharge of each waste source is specified with an aim to establish balance between different units. In fact, one can establish different costs for different levels of the equity index. It is noteworthy that, non-violation of the standard dissolved oxygen value in the river path is for the inequity index establishment. As mentioned, a constraint on the optimization problem in this model is non-violation of the standard dissolved oxygen value. It is clear that for the obtained solutions, the part ranges from maximum equity against spending high costs to minimum treatment percentage required to create a non-violation of standard dissolved oxygen value (which is equivalent to establishing minimum equity index). In other words, the more the money spent in the relevant part, the higher will be the equity between treatment units. Moreover, according to obtained charts, it can be said that the LC solution in Fig. 2 is the same as the solution obtained at the point non violation with least cost (NVLC) which corresponds to the minimum cost required for non-violation of the standard dissolved oxygen value in the entire path. The leas inequity (LIE) point actually represents the establishment of maximum equity with spending more costs and the mean treatment of 87 percent when there is no violation of the standard dissolved oxygen between treatment units. The details are given in table 3. Each discharger unit can select its drain strategy from possible treatment scenarios. Scenarios are defined based on the total treatment cost in the system. In this way, scenario 1 is defined with a cost of M$ 3 and scenarios 2, 3 and 4 with costs of M$ 3.5, 4, 4.5 in the whole system to allocate waste load by establishing the lowest inequity between dischargers. Details about each of these scenarios and their costs are given in Table 4. Moreover, Fig. 4 shows a profile of dissolved oxygen in the river length for the case there is no violation of the standard it represents dissolved oxygen for the case that industries without treatment discharge wastewater into the river. Fig. 5 represents the dissolved oxygen during the river at the NVLC case for the cost-violation model and Fig. 6 represents dissolved oxygen during the river for the case that there is no violation of the standard and shows the least inequity value between dischargers. As a result quality of the water river has been improved by establishing equity in system. In order to evaluate the performance of MOPSO for waste load allocation problems, the comparison was accomplished using MOPSO and Non-dominated Sorting Genetic Algorithm-II (NSGA-II). Numerical results that are

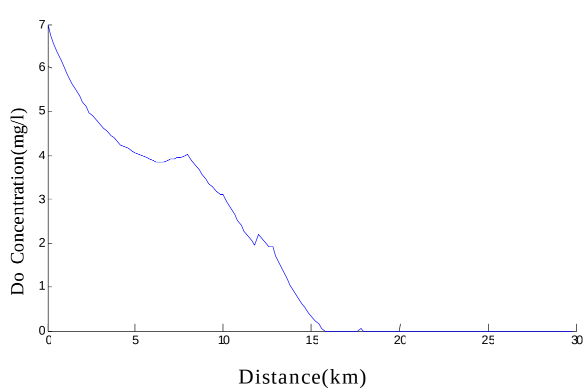

Fig. 5. DO profile for NVLC

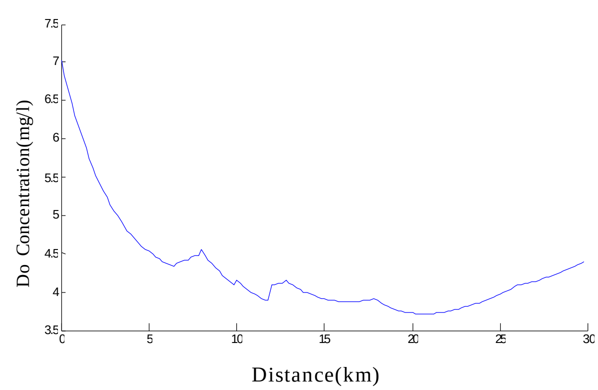

Fig. 6. DO profile for LIE

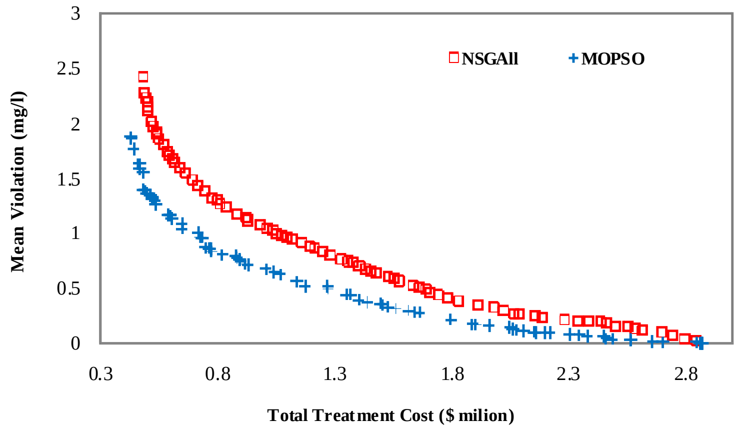

Fig. 7. Pareto front of MOPSO and NSGA-II on Cost versus Quality Model

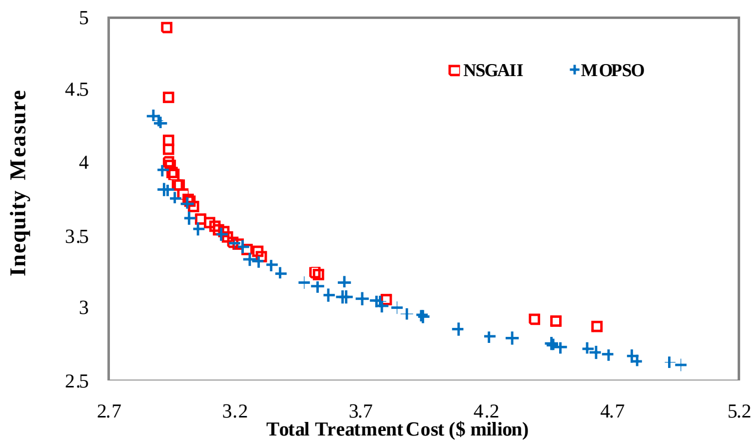

Fig. 8. Pareto front of MOPSO and NSGA-II on Cost versus Inequity Measure

also compared with NSGA-II show the advantages of this approach. Fig.7 shows all non-dominated solutions achieved by MOPSO, are most optimum in comparison with the solutions obtained by NSGA-II, while both algorithm have the same convergence. Fig.8 shows the two algorithms converge to the Pareto optimal front. MOPSO is considerably better than NSGAII in terms of Diversity Measure.(Niu, Wang *et al*. 2012) NSGA-II has a problem in finding the entire pareto-optimal front. However, MOPSO performs well, obtaining non-dominated solutions spread over the entire regions. It is important to notice the very high speed of MOPSO, which is almost 8 times faster than the NSGA-II in this problem, this will be remarkable if we consider the NSGA-II as a "very fast" algorithm (Coello, Pulido *et al*. 2004). The results show that the average computational times in minutes required for each algorithm run are 1.12 and 8.51, for MOPSO and NSGA-II, respectively. It may notice that, the total number of objective function evaluations was set equal to 7000, 70 population size and 100 iterations for both algorithms. Both the algorithms were run at the same PC an Intel Core i5 at 2.53 GHz with 4-GB RAM.

CONCLUSIONS

In this study, Multi-objective Particle Swarm Optimization (MOPSO) algorithm was applied to minimize the pollutant treatment costs in river waste load allocation in regard to the environmental standard violation and inequity criteria. There, it was concluded that this approach can well be used for multi objective optimization even in comparison with NSGA-II as a result MOPSO converges fast to the true optimal trade-off, and at same time preserves good diversity along the pareto-optimal front. Also, it is recommended that the equity levels can be used to have a fair waste load allocation policy in water basin. However, the latter may not lead into a more economical result. Consequently, a waste reallocation is introduced to achieve more economical results while the equity is at maximum level. Moreover, this study has the potential to be developed by water quality trading approach to find a more integrated policy making.

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