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CHARGED SYSTEM SEARCH FOR OPTIMUM DESIGN OF COST-EFFECTIVE STRUCTURAL BEST MANAGEMENT PRACTICES FOR IMPROVING WATER QUALITY

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ABSTRACT

Best Management Practices (BMPs) are implemented in a watershed to reduce the amount of non-point source pollutants transported to water bodies. However, an optimization algorithm is required to choose the efficient type, size, and location of BMPs for application in a watershed for improving the water quality. In this study, the Charged System Search, a well-known and powerful meta-heuristic optimization algorithm, as an optimization model and a semi-distributed hydrological model i.e. Soil and Water Assesment Tool (SWAT) were coupled to obtain cost-effective combination of different BMPs. To demonstrate the performance and applicability of the coupled model, it was utilized to Sofichai watershed upstream of the Alavian Reservoir in the northwestern part of Iran to compare four reduction levels of sediment, nitrate nitrogen and phosphate phosphorous loads at the watershed outlet.

Keywords: charged system search; soil and water assesment tool; best management practices; watershed

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1. INTRODUCTION

Non-point source (NPS) nutrient pollution, especially nitrogen and phosphorus, has become a principal environmental issue in many countries, due to the prevalent eutrophication of water bodies [1]. So, controlling and reducing nutrient loads at the watershed scale seems necessary to improve the quality of water bodies. Watershed models allow natural resource managers to find out natural processes taking place at the watershed scales and simulate the influence of different management scenarios on soil and water resources [2].

A comprehensive review of eleven widely used present-day hydrologic and water quality models was done by Borah and Bera [3]. They found that Soil and Water Assessment Tool

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(SWAT) and Simulation Program – Fortran (HSPF) are suitable for the simulation of the flow, sediment and nutrient loads, however they need to diverse source of information and empirical parameters.

Best Management Practices (BMPs) are both structural or non-structural practices applied in a watershed to control runoff, sediment, and nutrients. Structural BMPs are usually appropriate in agricultural watersheds consist of detention ponds, grassed waterways, filter strips, grade stabilization structures, and field terraces. SWAT is capable to model the effectiveness of several BMPs in reducing the sediment, and nutrient loads in a watershed. In order to find the optimal combination of BMPs, it is essential to an optimization algorithm coupled with SWAT model. Therefore, using a meta-heuristic optimization algorithm could aid as an effective approach in order to diminish the watershed sediment and nutrient loads with a possible least cost.

Srivastava et al. [4] coupled Genetic Algorithm (GA) with Annualized Agricultural Non-Point Source Pollution model (AnnAGNPS) to design an ideal crop rotation practices to maximize either pollution reduction or net return but not simultaneously, in a small watershed. Veith et al. [5] compared a GA-based optimization model and targeting strategies to allocate cost-effective land use and tillage practices. The cost related to optimization model was lower than targeting with equivalent NPS reduction. Muleta and Nicklow [6] integrate a GA-based multi-objective optimization model with SWAT to select efficient crop rotation and tillage operations at a watershed. Arabi et al. [7] linked GA and SWAT to find cost-effective combination of four structural BMPs with respect to extreme monthly sediment, phosphorus, and nitrogen loads. Kaini et al. [8] and Artita et al. [9] integrate SWAT with GA to reduce peak flow and sediment load. Maringanti et al. [10] applied a multi-objective GA and SWAT model to find optimal location of BMPs to minimize both a pesticide concentration and the cost of BMPs. Karamouzet al. [11] applied an integrated GA-based optimization model with coupled watershed-reservoir model to reduce phosphorus load to the reservoir through BMPs implementation in Ahar chai watershed. They used SWAT and system dynamic model to simulate watershed phosphorous load and reservoir phosphorous concentration.

Kaini et al. [12] linked genetic algorithm with SWAT to optimize combination of structural BMPs to reduce sediment and nutrients at the watershed outlet in three different reduction level cases with a minimum cost. Emamiskardi et al. [13] utilized an ant colony optimization algorithm (ACO)-based SWAT model to find optimal size of detention ponds with minimum cost and minimum amount of total suspended solids (TSS).

Although improvement of water quality through application of BMPs in the watershed level has been considered in many researches, applying a new meta-heuristic optimization algorithm is almost rare. This paper aims to cover this advantage by using Charged System Search (CSS) algorithm as a powerful optimization technique introduced by Kaveh and Talatahari [14]. The CSS takes inspiration from the governing laws of electrostatics and motion form mechanics. This algorithm has been applied to various types of problems such as optimal design of skeletal structures [15], optimum design of composite open channels [16], optimal cost design of water distribution networks [17] and regret-based TMDL optimization under climate change in New River [18]. Using this algorithm is growing and expanding diverse optimization problems. In the following, a brief description of materials and methods consists of the CSS algorithm, SWAT model, BMPs representation to model

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and case study area are presented. Then, the formulation of watershed optimization problem is defined. Finally, the numerical results obtained by the integrated new model (CSS-SWAT) are evaluated.

2. CHARGED SYSTEM SEARCH ALGORITHM

The CSS algorithm has some charged particles (CPs) as agents, where each agent (CP) is assumed as a charged sphere with radius a and a uniform volume charge density which can exert force on any other agents [14]. The force is directly proportional to the product of two agent's charges and is inversely proportional to square of distance between two agents. The optimization procedure in the CSS algorithm is based on calculating the resultant force exerting on each CP, and then agents are moved to their new positions according to the Newtonian laws of motion. These sequential movements of the CPs guide the algorithm toward optimum solutions. The following steps explain the CSS algorithm:

Step 1: Initial positions of agents and their related velocities identified randomly.

$$x_{i.j}^{(o)} = x_{i.min} + rand \cdot (x_{i.max} - x_{i.min}). \quad i = 1.2. \dots . n \tag{1}$$

where $x_{i.j}^{(o)}$ defines the initial value of the ith variable for the jth CP,$x_{i.min}$ and $x_{i.max}$ are the minimum and maximum permissible range for the ith variable; *rand* is a random number between 0 and 1; and *n* is the number of variables. The initial velocities of particles are considered zero. In order to improve performance of CSS algorithm, a memory named charged memory is considered to save the best CP vectors and their associated objective function values. In this paper, the size of the CM is assumed to be *N*/4 (*N* is the number of agents).

Step 2: The force vector exerted on each CP is calculated as below:

$$F_j = q_j \sum_{i.i \neq j} \left(\frac{q_i}{a^3} r_{ij} \cdot i_1 + \frac{q_i}{r_{ij}^2} \cdot i_2 \right) p_{ij} \left(X_i - X_j \right). \quad \begin{cases} j = 1.2. \dots . N, \\ i_1 = 1.\ i_2 = 0 \Leftrightarrow r_{ij} < a. \\ i_1 = 0.\ i_2 = 1 \Leftrightarrow r_{ij} \geq a. \end{cases} \tag{2}$$

where F_j is the resultant force exerting on the jth CP, r_{ij} is distance between two charged particles is determined as follows:

$$r_{ij} = \frac{\left\| X_i - X_j \right\|}{\left\| (X_i + X_j)/2 - X_{best} \right\| + \varepsilon} \tag{3}$$

where X_i and X_j and X_{best} are the positions of the ith,jth and the best current CP respectively. ε is a small positive number for dealing with the problem of singularities. The probability(p_{ij})oftransition each CP towards the others is calculated using the following function:

$$p_{ij} = \begin{cases} 1 & \frac{fit(i) - fitbest}{fit(j) - fit(i)} > rand \vee fit(j) > fit(i) \\ 0 & else \end{cases} \tag{4}$$

The charge density of each CP is defined as below:

$$q_i = \frac{fit(i) - fitworst}{fitbest - fitworst}. \qquad i = 1.2 \ldots. N \tag{5}$$

$fitbest$ and $fitworst$ are the best and worst fitness (objective function) value of all particles, $fit(i)$ is the fitness of ith CP, and N is the total number of CPs agents.

Step 3: The new positions of CPs are determined based on the resultant force and motion laws.

$$X_{j.new} = rand_{j1} \cdot k_a \cdot \frac{F_j}{m_j} \cdot \Delta t^2 + rand_{j2} \cdot k_v \cdot V_{j.old} \cdot \Delta t + X_{j.old} \tag{6}$$

$$V_{j.new} = X_{j.new} + X_{j.old} \tag{7}$$

where k_a and k_v arethe acceleration and velocity coefficients; m_j is the mass of the jth CP which is set to q_j. Δt is the time step and is assumed to be unity.

Step 4: If the new position of each CP is out of the search space, its position is modified by using harmony search approach[19-20]. Furthermore, if some CP objective values related to their new positions are better than the worst ones in the CM, they are replaced instead of the worst ones in the CM.

Step 5: Steps 2 through 4 are repeated up to an ending criterion is fulfilled.

Original CSS has been presented for continuous domain structural problems. A discrete CSS algorithm was introduced to improve its ability in solving discrete problems[21].One modification to adapt CSS for discrete optimization problems is to use a function which rounds the real value to the nearest discrete value, as:

$$X_{j.new} = Fix\left(rand_{j1} \cdot k_a \cdot \frac{F_j}{m_j} \cdot \Delta t^2 + rand_{j2} \cdot k_v \cdot V_{j.old} \cdot \Delta t + X_{j.old}\right) \tag{8}$$

This change will diminish the exploration ability of the CSS. Hence, to keep the exploration ability, two changes are applied. Initially, a new parameter defined to identify the type of force as:

$$ar_{ij} = \begin{cases} +1 & w.p.\ k_t \\ -1 & w.p. 1 - k_t \end{cases} \tag{9}$$

Adding this new parameter will change the resultant force as follows:

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$$F_j = q_j \sum_{i.i\neq j} \left(\frac{q_i}{a^3} r_{ij} \cdot i_1 + \frac{q_i}{r_{ij}^2} \cdot i_2 \right) ar_{ij}\, p_{ij} \left(X_i - X_j \right). \quad \begin{cases} j = 1.2. \dots . N, \\ i_1 = 1.\ i_2 = 0 \Leftrightarrow r_{ij} < a. \\ i_1 = 0.\ i_2 = 1 \Leftrightarrow r_{ij} \geq a. \end{cases} \tag{10}$$

Secondly, the value of $k_v$increased to improve exploration rate of the CSS.

3. THE SOIL AND WATER ASSESSMENT TOOL (SWAT) MODEL

3.1. Presenting the model

The soil and water assessment tool (SWAT) [22-23] is a physically based, semi-distributed, continuous time model that operates on a daily time step and simulates the transition of water, sediment, and nutrients at a watershed level. SWAT is capable to assess the effectiveness of diverse management scenarios on flow, sediment, and water quality.

Runoff is determined individually for each hydrological response unit (HRU), the finest unit with unique land use, soil, and slop, then accumulated to the sub-basin level and routed through the main channel to acquire the total runoff for the watershed. Also, SWAT has algorithms for simulating erosion using the Modified Universal Soil Loss Equation (MUSLE). The transformation process in the soil of agricultural nonpoint source pollutions such as nitrogen and phosphorus is simulated in SWAT. In addition, SWAT uses QUAL2E model [24] to simulate and route nutrients in the stream.

3.2. Structural best management practices in SWAT

SWAT has a capability to integrate diverse structural and non-structural BMPs at the same time, and simulate their effects at watershed level. The structural BMPs applied in this study consist Detention Ponds (DP), Filter Strips (FS), Parallel Terraces (PT), and Grade Stabilization Structures (GSS).

A DP is a permanent pond placed within a sub-basin to retain inflow from a fraction of the sub-basin area for a certain time. It can decrease the sediment and nutrients load by sedimentation and biological process. In this study, DP with the impermeable bottom was used. The fraction of the sub-basin drains to the pond, pond area and pond volume are parameters to represent DP in SWAT.

A filter strip (FS) is used widely to trap sediment and pollutants before entering water bodies. In the recent version of SWAT, the filtering efficiency for sediment and nutrients are different unlike previous version [25]. The parameter related to filter strip in SWAT is the width of edge of field filter strip (FILTERW).

Parallel terrace is designed in a HRU by earthen ridges or channels to reduce surface runoff volume, peak runoff rate and to increase settling of sediments in surface runoff. In order to model parallel terrace, the soil conservation service curve number (*CN*2), Universal Soil Loss Equation (USLE) support practice factor (USLE_P) and average slope length (SLSUBBSN) parameters will be modified in SWAT [26-27].

Grade stabilization structures (GSS) are applied to control the grade of channels. Implementation of grade stabilization structures will decrease the channel slope, channel erodibility and flow velocity, consequently sediment trapping will be increased. GSS will be

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presented to SWAT with modifying the channel segment ($CH - S2$) and channel erodibility factor($CH - EROD$).

In this study, all representative parameters for the BMPs applied in the optimization model beside their values changed in pre- and post–BMP conditions are listed in Table 1. Pre-BMP values are the calibrated values of the parameters with no BMP. The unit costs of four BMPs applied in this study are presented in Table 2, [12].

Table 1: Model parameter used to represent pre-BMP and post- BMP conditions

BMP TYPE	**Parameters**	**SWAT input file**	**Pareameterdescription**	**Pre-BMP (from calibration)**	**Post-BMP**
Filter Strip (FS)	FILTERW	.hru	Filter Width (m)	0	20
Parallel terraces (PT)	CN2	.mgt	SCS Runoff CN	varies	(CN2)-6
	USLE-P	.mgt	USLE equation support practice factor	0.35-0.5	a
	SLSUBBSN	.hru	Average Slope Length	10-150	a
Grade Stabilization Structure (GSS)	CH-S2	.rte	Channel slope steepness	varies	Reduced by 10%
	CH-EROD	.rte	Channel erodibility factor	0.44	0.001 (nonerodable)
Detention Pond (DP)	Pnd_Fr	.pnd	Fraction of HRU draining to pond	0	0.9
	Pnd_Psa	.pnd	Surface area of ponds when filled to principal spillway (ha)	0	(0.005, 0.0075, 0.01, 0.02) of each subbasin area
	Pnd-Pvol	.pnd	Volume of water stored in ponds when filledto the principal spillway (10^4 m^3)	0	Depth of Pnd (3, 3.5, 4) *Pnd_Psa

Table 2: unit cost of BMPs

BMP	Description	Unit	Unit Cost (US$)
1	Detention ponds (DP)	Acre-ft	500
2	Grade Stabilization Structures (GSS)	Number	6000
3	Parallel Terraces (PT)	Acre	500
4	Filter Strips (FS)	Acre	250

4. THE STUDY AREA AND SWAT MODEL DEVELOPMENT

Sofichai watershed is a part of the Lake Urumia basin. It is located in northwestern Iran between 37° 11'- 38° 28' N and 46° - 46° 25' E.The watershed covers an area of 313 km^2up to Alavian Dam (Fig. 1).

The initial SWAT model set-up requires a digital elevation model (DEM), land-use/land-cover, soil data, and meteorological data which were obtained from different sources. DEM was provided from the Iranian surveying organization with 1:25000 scale. Land-use map of the watershed was generated using MODIS satellite imageries. The Soil map was extracted from the global soil map of Food and Agriculture Organization of United Nations

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(FAO,1995) with 1:5000,000 scale. The weather-generator variables were obtained from Iranian Meteorological Organization for Marageh and Tabriz synoptic stations near the watershed. Time spans covered by the available data were from 1983 to 2013. Daily precipitation data of Ashan and Alavian rain gauge stations in the watershed were available only for the period 1999-2012. Additional data such as relative humidity, wind speed, solar radiation were generated by the SWAT weather generator.

In this study, the watershed of Sofichai was divided into 41 sub-basins by using a threshold value of 400 ha. These sub-basins further divided into 144 HRUs based on the land-use, soil and slope. After providing the required data files and information layers, the SWAT model was run from 1999 to 2012 based on the limitation of precipitation data. We have used the ArcSWAT2012 version of SWAT model interface with ArcGIS 10.1 of ESRI product for processing the analysis.

SWAT model calibration and uncertainty analysis for daily flow, daily sediment, daily Nitrate nitrogen, and daily Mineral phosphorous was performed with SWAT-CUP [28]and Sequential Uncertainty Fitting (SUFI-2) algorithm. There was a data limitation in model calibration of sediment and nutrients. Availability of observed sediment and nutrients data were one of the major limitation as only 107 and 60 sediment and nutrients data were used for calibration and validation. A model performance was considered to be good for values of Nash Sutcliffe coefficient of efficiency (NSE) greater than 0.75, while for values of 0.36<NSE<0.75, model performance was considered to be satisfactory [29]. For this study, the model performance between simulated and observed data was generally considered satisfactory for calibration and validation periods.

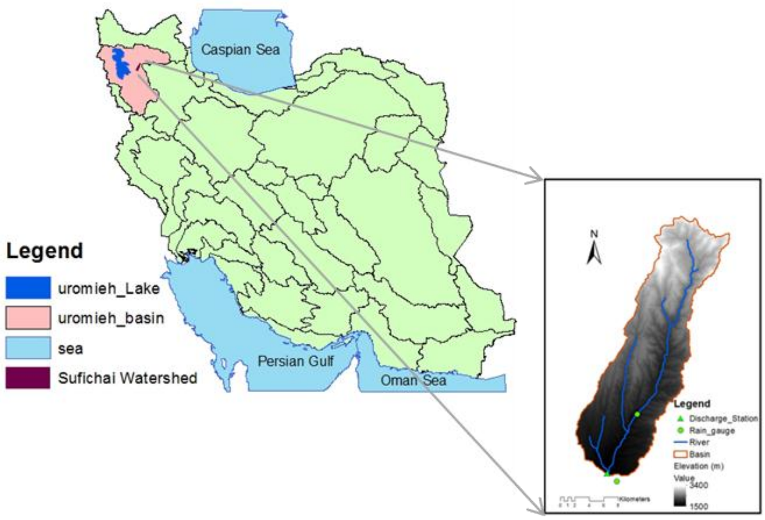

Figure 1. Location map of sufichai watershed

5. Problem formulation

In this study, the optimization problem can be identified as the design of BMPs (type, size, and location) at watershed level and is expressed as follows:

$$Minimize\!: TCBMP = \sum_i \sum_j CBMP_{ij} \ \ Subject\ to\!:\ \ RTSSL_{mean} \geq RTSSL_{\min\ lim} \tag{11}$$

$$RNutL_{mean} \geq RNutL_{\min\ lim} \quad TSSL_{mean} = g(x,u,t) \ \ NutL_{mean} = h(x,u,t) \tag{12}$$

where, $TCBMP$ is the total cost of BMPs applied in the watershed.$CBMP_{ij}$ is the cost of a j type of BMP applied in sub-basin i or HRU i. $RTSSL_{mean}$ and$RNutL_{mean}$ are the reduction of the mean annual sediment and nutrients load during simulation period, respectively. $RTSSL_{\min\ lim}$ and $RNutL_{\min\ lim}$ are the user-defined minimum reduction limit of mean annual sediment and nutrients load, respectively. The last two equations signify simulation constraints, where $g$and $h$in generalsignifies all relevant hydrologic and hydraulic relations, as a function of state (x),decision (u)variables and time t. BMP parameters as decision variables are listed in Table 1.

The proposed procedure integrates the SWAT model as a watershed simulator with CSS as a meta-heuristic optimization algorithm to design BMPs at the watershed scale. The design procedure was initiated by choosing random values for decision variables. Then, SWAT model simulates response of the watershed to BMPs implementation and the optimization algorithm examines the reduction constraints and estimates their related cost (Fig. 2).

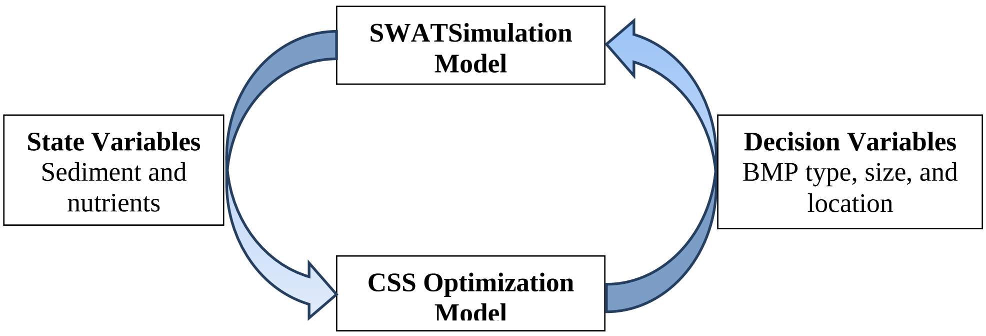

Figure 2. Schematic representation of simulation-optimization model

In order to handle the constraint, a penalty method was operated. If the constraints were in the permissible range, the penalty was considered zero; otherwise the amount of penalty was acquired by dividing the violation of permissible range to the range itself, as:

$$TCV = \frac{RTSSL_{\min\ lim} - RTSSL_{mean}}{RTSSL_{\min\ lim}} + \frac{RNutL_{\min\ lim} - RNutL_{mean}}{RNutL_{\min\ lim}} \tag{13}$$

$TCV$is the total constraint violation. In this paper, the amount of penalty cost for infeasible solutions was determined as below:

$$Penalty = \alpha \times TCV \tag{14}$$

$\alpha$is the penalty parameter with a large adequate value to guarantee that any infeasible result will have a higher total cost than any feasible result. Here, the penalty parameter was considered as the cost of BMPs when applied on all HRUs/Sub-basins (about 1.4×10^7).

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The total cost was then estimated as the sum of the BMPs application cost and the penalty cost.

$$Minimize: BMPC = \sum_i \sum_j BMPC_{ij} + Penalty \qquad (15)$$

6. RESULTS AND DISCUSSION

A simulation-optimization model shown in Fig. 2 was developed to allocate four types of structural BMPs in the Sofichai Watershed. These BMPs included Detention ponds, Filter Strips, Parallel Terraces, and Grade Stabilization Structures. The analysis aimed at assigning BMPs such that the reduction of mean annual sediment and nutrients loads satisfy the corresponding reduction case with a minimum cost at the watershed outlet.

In the optimization model, constraints of CSS included water quality constraints that were set to the reduction cases (15%, 30%, 50%, and 70%). The model was applied for four different reduction cases individually and their results were compared in terms of cost and number of BMPs required. In this study, the population is set to 50 and the maximum number of allowed iterations is equal to 300. The values of HMCR and PAR parameters for harmony search approach were considered as 0.95 and 0.1, respectively [19].

HRUs with agricultural land use are qualified for filter strip implementation. Out of 144 HRUs, 62 are qualified for Filter strip implementation. Parallel Terraces are applicable to some HRUs based on land use and slope of HRUs. Table 3 shows the optimum combination of BMPs in the Sofichai watershed. The minimum cost for overall BMPs combination and the sediment and nutrient loads at the watershed outlet in four reduction cases were presented in Table 4. Comparing four reduction cases showed that the minimum cost and the number of BMPs required increases as the criteria for sediment and nutrients reduction increases.

Table 3: The best solutions of four reduction cases

BMP type	>15%	>30%	>50%	>70%
Detention ponds	0	1	7	8
Grade Stabilization Structures (GSS)	0	0	0	0
Parallel Terraces (PT)	0	0	0	0
Filter Strips	34	34	62	62
Total number of BMPs	34	35	69	70

Table 4: the cost of best solutions and sediment and nutrient loads in all reduction cases

	No reduction case	15%	30%	50%	70%
Minimum COST (10^6 US$)	-	0.161	0.426	1.23	2.36
Sediment Load (tons/year)	28866	24247	19746	13112	8660
N-NO3 Load (kg/year)	40569	28398	27881	20828	20828
P-PO4 Load (kg/year)	2215	1550	1536	1373	1373

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Fig. 3 and 4 shows graphical presentation of optimal spatial allocation of BMPs in four reduction cases. The convergence of CSS algorithm to optimize the cost of BMPs in 15% and 30% reduction cases are shown in Fig. 5, while Fig. 6 shows the convergence of the CSS algorithm for 50% and 70% reduction cases.

CSS found the best feasible solution of 0.161×10^6 \$ and 0.426×10^6 \$ after 154 and 265 iterations for 15% and 30% reduction cases (Fig. 5). In the reduction case of 15%, only 34 filter strips were implemented in the watershed and the optimum combination of BMPs resulted in about 17%, 31%, and 31% reduction in annual sediment, Nitrate nitrogen (N-NO3) and Mineral phosphorus (P-PO4) loads, respectively. For 30% reduction case, model assigned 34 filter strips in the watershed plus 1 detention pond to reduce more than about 30% reduction in all pollutants.

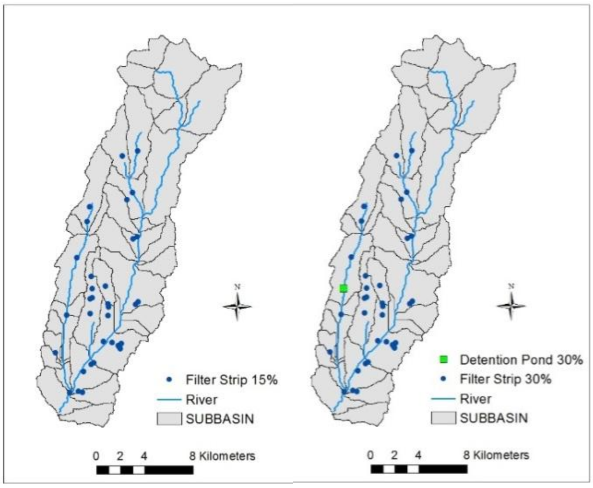

Figure 3. BMPs distribution for 15% and 30% reduction cases

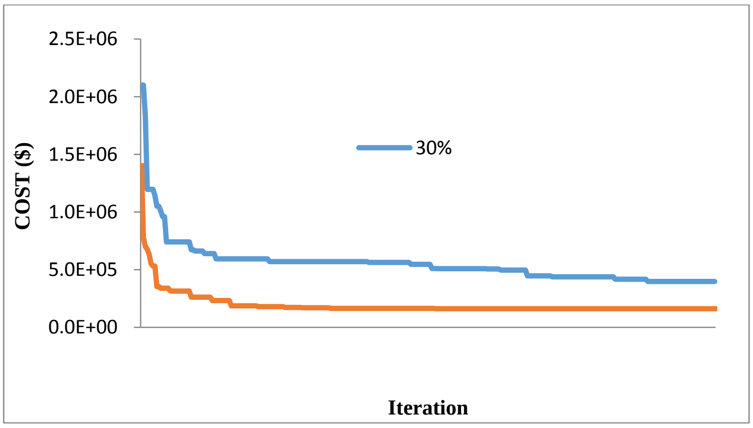

Figure 4. The convergence history of CSS algorithm to optimize the cost of BMPs in 15% and 30% reduction cases

For both 50% and 70% reduction cases, the optimization model could not find a feasible solution. The minimum cost for overall BMP combinations were 1.23×10^6 \$and $2.36 \times$

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10^6 \$with minimum violation after 280 and 286 iterations for 50% and 70% reduction cases (Fig. 6). In the reduction case of 50%, model assigned 62 filter strips and7 detention ponds in the watershed, while in 70% reduction case, 62 filter strips and 8 detention ponds were assigned. The optimum combination of BMPs resulted in about 54%, 48%, and 38% reduction in annual sediment, Nitrate nitrogen (N-NO3) and Mineral phosphorus (P-PO4) loads, respectively. The reduction amount of annual sediment, Nitrate nitrogen and Mineral phosphorus loads were about 71%, 48%, and 38% in 70% reduction case. As it is clear, the constraints of optimization model in 50% and 70% reduction cases were not satisfied. In both cases, the reduction percent of Nitrate nitrogen and Mineral phosphorus loads and the number of the HRUs in which filter strips were implemented were equivalent. The volume of detention ponds applied to the watershed for 70% reduction case was about two times more than in 50% reduction case. Therefore, the maximum annual reduction percent of nutrients were equal to about 48% and 38% for N-NO3 and P-PO4 loads. Also, it was clear that filter strips and detention ponds were two effective BMPs in this watershed. Detention ponds were effective to reduce sediment, while filter strips could reduce all nutrients effectively.

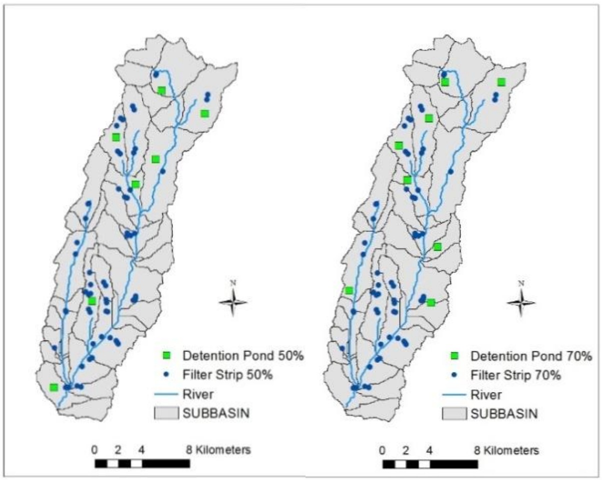

Figure 5. BMPs distribution for 50% and 70% reduction cases

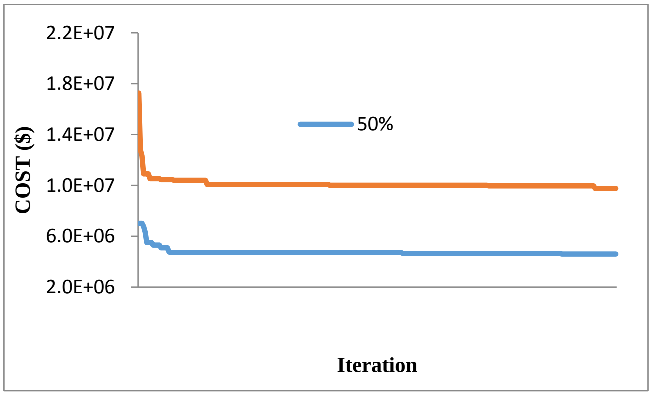

Figure 6. The convergence history of CSS algorithm to optimize the cost of BMPs in 50% and 70% reduction cases (cost with penalty)

6.1 Comparing CSS with other methods

In order to assess the performance of the CSS, other meta-heuristics algorithms such as Genetic Algorithm (GA), Colliding bodies optimization (CBO) [30], Enhanced colliding bodies optimization (ECBO) [31], Particle Swarm Optimization (PSO) [32], and Vibrating particles system (VPS) algorithm [33] were used for 50% reduction on annual sediment, Nitrate nitrogen (N-NO3) and Mineral phosphorus (P-PO4) loads at the watershed outlet. For all algorithms, the number of agents and iterations were the same. Fig. 7 shows the optimal cost obtained with six algorithms. According to Fig. 7, the best solution was found by CSS. VPS obtained solution close to CSS, while GA resulted in a solution with 2.6 times higher than the CSS solution. Fig. 8 shows the convergence history of six mentioned algorithms in 50 iterations. It is apparent from the Fig. 8 that the CSS algorithm has the fastest convergence rate compared to other ones. VPS had slower convergence rate than CSS, although the results were approximately closer.

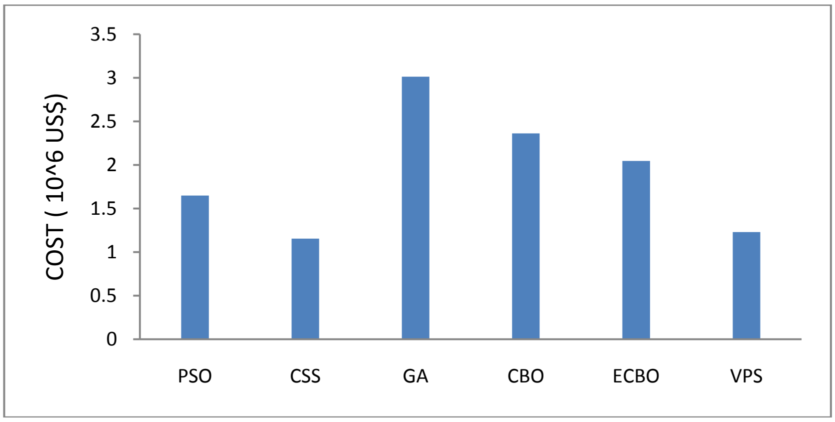

Figure 7. Performance comparison of methods for the 50% reduction case

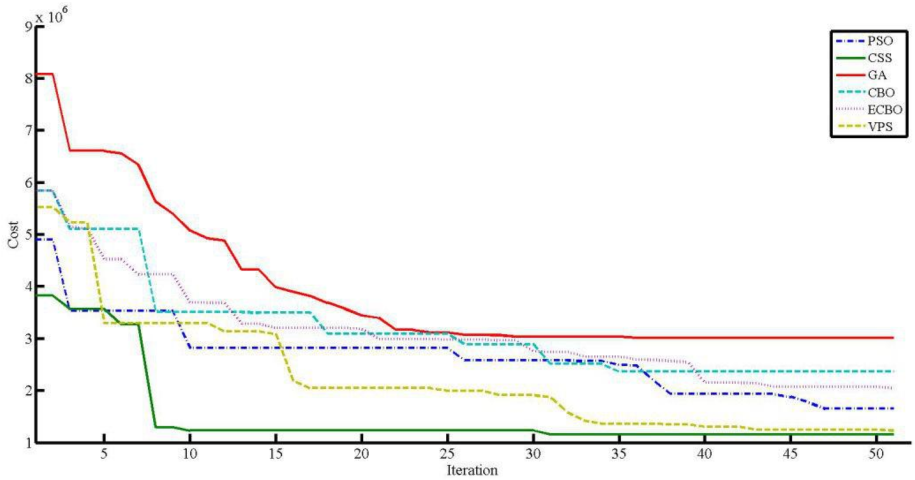

Figure 8. Comparison of the convergence rates of the CSS algorithm with other algorithms for the 50% reduction case

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7. CONCLUSIONS

For the first time, the discrete charged system search (CSS) was used for cost optimization of Best Management Practices (BMPs) in the watershed. The optimal design of BMPs is computationally complicated and the result of applying charged system search algorithm for Sofichai watershed provided promising results. The influence of structural BMPs on water quality was evaluated by SWAT model which is integrated with CSS algorithm. Integrated model of CSS-SWAT was able to search for least cost combination of BMPs in order to reach 15%, 30%, 50%, and 70% reduction of sediment and nutrient loads. The results showed among the considered BMPs, filter strip was the most chosen BMPs in all annual sediment, N-NO3 and P-PO4 reduction loads; while parallel terraces and grade stabilization structures were the least chosen options. Also, the comparison of the results of the CSS with other methods such as, GA, CBO, ECBO, PSO, and VPS demonstrated the performance and efficiency of the CSS algorithm in finding the optimal combination of type, size and spatial location of BMPs. In addition, CSS showed high convergence rate in the initial iterations compared to the other algorithms.

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