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Regret-Based Decision Making for Total Maximum Daily Load Allocation under Climate Change Scenarios; Application of Charged System Search Algorithm

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Abstract

Although temporal and spatial severity of climate change remains uncertain, its occurrence and impacts on water resources is quite perceivable. Under any uncertain condition, such as climate change, proper and sustainable pollutant load allocation to receiving water bodies remains as a serious challenge. In the absence of statistical data and reliable probability distribution function for uncertain parameters, planners may use non-probabilistic approaches for tackling the imposed uncertainties. Among the common non-probabilistic approaches, the regret method is a robust and successfully used method for decision analysis. This paper presents an integrated approach for pollutant load allocation under uncertain climate condition. It integrates an efficient optimization algorithm and a physical quality simulation model in a regret-based decision analysis platform. The proposed system establishes a linkage between loads and receiving water conditions to maximize the dischargeable total maximum daily load (TMDL). Water quality responses of the receiving water body under different loads are estimated using QUAL2K simulation model. Maximization of total daily load under varying scenarios is carried out with the charged system search (CSS) algorithm. Effects on uncertainties in occurrence and severity of the assumed scenarios are analyzed in a non-probabilistic framework with minimizing the maximum and total regret (MMR, MTR), and the best scenario is proposed for implementation. Performance of the proposed approach is tested using the data from New River at the Salton outlet.

Keywords: Pollutant Load Allocation, Climate Change, Regret Analysis, Charged System Search Algorithm, Uncertainty, Robust, Total Maximum Daily Load, TMDL.

1. Introduction

Although temporal and spatial severity of climate change remains uncertain, its occurrence and impacts on water resources is certain. Any perceivable change in the quantity of running water bodies will affect its self-cleaning capacity and spatial and temporal quality variation. Under any uncertain environment, the authorities are faced with the challenge of temporal and spatial allocation of pollutants to water bodies and the resulting discharge permits under prevailing and climate change condition. Therefore, specialists must either explicitly or implicitly account for the uncertainties involved to plan for the most appropriate load allocations. Uncertainty may be part of the environment in which the decision is being made or it may be associated with the outcomes from the actions or decisions made. In an uncertain situation, either the set of outcomes is unknown or agreement as to a probability distribution cannot be reached. In these cases, the probability theory may lose its merits in uncertainty analysis. In case of climate change, a random number with defined probability density function may not describe the outcome.

In the case of non-statistical uncertainties, the probability theory should be replaced with appropriate approaches which fit the problem. Under these circumstances, possibility approach (i.e., fuzzy theory) and regret minimization are effectively used. Although number of classical methods for explicit incorporation of risk and uncertainties into decision-making process are available, they often require probability distribution to assign probability values to different future conditions (Byer et al., 2009).On the other hand, during the last decade, non-probabilistic methods, such as regret methods, have been applied to civil and environmental engineering problems (Afshar and Najafi, 2014, Afshar and Amiri 2010, Maass et al., 1962). Regret theory intends to minimize a function of the regret vector defined as the difference between the outcome of a given choice and the best outcome that could have been achieved in that state of nature. When the likelihood of the possible outcomes cannot be predicted and/or assumed, the regret approach offers reliable criteria for decision making under uncertainties (Loulou and Kanudia, 1999).

Assessment and evaluation of loading capacities that will meet water quality standards often support the development of Total Maximum Daily Load[1]. The purpose of a TMDL program is to improve the water quality of the receiving water bodies by controlling both point and distributed contaminant sources, while optimally utilizing its capacity to receive pollutants from various sources. In other words, a TMDL may be recognized as a "pollution budget" designed to restore the health of the polluted water body.

In a comprehensive review on TMDL, many integrated models have been assessed considering the data processing, modeling tools, and supported model linkages (USEPA, 2005). The review concludes that extensive research is still needed to expand the capabilities, defensibility, and application of the models.

It emphasizes on the opportunity to capitalize on the management and processing of the new data and the enhanced performance of modern computers and internet communications (USEPA, 2005). In a robust modeling scheme, Chen et al developed a Decision Support System[2] to calculate TMDLs of various pollutants in a river basin (Chen et al., 1999). The system generates combinations of waste load and nonpoint- load allocations to facilitate the regulatory agency and local stakeholder's negotiation process on addressing the most desired option with highest agreement to all parties. To account for the interactions between key socioeconomic subsystems and natural processes supporting eutrophication, an integrated system dynamics model is developed (Mirchi and Watkins, 2013).

The EPA TMDL Modeling Toolbox is designed to selectively collect and combine the models, modeling tools, and databases developed for calculation of TMDL over the last decade. It has a modular structure such that each of the models has a stand-alone application. Therefore, integration of any new model into the tool is easily achievable. Besides the steady state dynamic simulation of water quality processes in all types of surface water bodies, it allows transfer of information between the models through common linkages. Although uncertainty analyses are identified as one of the top-priorities in the entire TMDL process (Maass et al., 1962, USEPA, 2005), employment of systematic uncertainty analysis within the TMDL process is relatively rare. Reviewing 172 TMDL reports and papers, Dilks and Freedman showed that only a few jobs directly utilized an uncertainty analysis to justify the Margin of Safety[3] used in the analysis (Dilks and Freedman, 2004). In a series of papers, the genetic algorithm, Hydrologic Simulation Program Fortran[4] and the Generalized Likelihood Uncertainty Estimation[5] techniques are combined to perform robust optimization of TMDL allocations and predict the reliability of compliance associated with each allocation policy (Jia and Culver, 2006, Taher and Culver, 2008, Taher and Culver, 2007).

Among the non-probabilistic approaches to uncertainty analysis, the regret methods have

[1] Total Maximum Daily Load (TMDL)

[2] Decision Support System (DSS)

[3] Margin of Safety (MOS)

[4] Hydrologic Simulation Program Fortran (HSPF)

[5] Generalized Likelihood Uncertainty Estimation (GLUE)

successfully been used for decision making under uncertainties when the likelihood of the possible outcomes cannot be predicted with a satisfying accuracy (Loulou and Kanudia, 1999). Regret is a sense of loss by the decision maker knowing an alternative action would be profitable instead of the one that was taken (Mausser and Laguna, 1998). Minimization of Maximum Regret[1] and Minimization of Total Regret[2] are used in tackling uncertainties with non- probabilistic approach. The MMR addresses the decision with the best performance in the worst case (Aissi et al., 2009, Colombo and Byer, 2012). In fact, it addresses the decision which minimizes the maximum deviation between that decision and optimum decision for each scenario, over all nominated scenarios. As a complete explanation of different regret concepts, Colombo and Byer presented a complete review on making decision under uncertainties of climate change (Colombo and Byer, 2012). In an experimental setting, Loulou and Kanudia verified that outcomes of MMR strategy depend only on the extreme scenarios and are independent of the intermediate ones (Loulou and Kanudia, 1999).

This specification makes the approach computationally very efficient. Various versions of regret approaches have been used for climate policies and sensitivity (Willows and Connell, 2003, Kunreuther et al., 2013), damage estimation and mitigation cost (Hof et al., 2010), planning the agricultural water management under uncertainty (Du et al., 2012), and water distribution consequence management (Afshar and Najafi, 2014). In a fairly recent work, Chang and Davila applied MMR optimization to regional solid waste management system (Chang and Davila, 2007). Hof et al. applied the MMR criterion quantitatively using an integrated assessment model with extreme values for climate sensitivity, damage estimates and mitigation costs (Hof et al., 2010).

Although different versions of regret models have been applied to various problems under uncertainties, its utilization in waste load allocation has been reported in some river distribution problems (Poorsepahy-Samian et al., 2012). Realizing the uncertainties involved in occurrence of various future climate scenarios and their impacts on hydrological data, this paper presents a robust modeling approach to develop pollutant load allocation with TMDL approach in an uncertain environment. The proposed modeling scheme provides a “linkage” between loads and receiving water conditions while maximizing the allowable total daily load. The approach employs a non-probabilistic regret approach to account for the uncertainties involved in different climate change scenarios. Water quality responses are simulated with the QUAL2K model and the Charged System Search[3] algorithm is utilized for maximizing the total daily load under different uncertain scenarios. The CSS algorithm has been successfully applied to various water resources engineering and management problems (Asadieh and Afshar, 2019). Its robustness and performance in comparison with other meta-heuristic algorithms were examined for finding the optimum solutions in a few engineering problems (Kaveh and Talatahari, 2010). The outcomes of the simulation-optimization model provide the required input for the regret analysis.

2. Materials and methods

The proposed methodology consists of four main steps as illustrated in Fig. 1. First step calculates the TMDL and the load allocations using QUAL2K and CSS optimization algorithm. At the second step, Dissolved Oxygen[4] variations under each climate scenario is calculated with the assumption that discharge permits have been implemented under the base condition. At the next step, initial loads are reallocated under condition of each hypothetical scenario with the same procedure as the first step. Finally, the regret analysis is conducted considering the uncertainties in their occurrence as presented in the following sections.

2.1. TMDL-based initial load allocation

As described, TMDL is the maximum amount of a pollutant that a water body can receive and still meet water quality standards. It also seeks to allocate that load to the various sources of that pollutant. Pollutant sources are often characterized as either point sources that receive a Waste Load Allocation[5], or nonpoint sources that receive a Load Allocation[6], which include both anthropogenic and natural background sources of the pollutant. TMDLs must also include a MOS to account for seasonal variations and the uncertainty in predicting how well pollutant reduction will result in meeting water quality standards. The TMDL may be calculated as

$$\text{TMDL} = \Sigma \text{WLA} + \Sigma \text{LA} + \text{MOS} \qquad (1)$$

Where

$\sum$WLA is the sum of waste load allocations from point sources; $\sum$LA is the sum of load allocations from nonpoint sources and existing background condition, and MOS defines the margin of safety. The purpose of a TMDL program is to improve the water quality of the receiving water bodies by controlling both point and distributed contaminant sources, while optimally utilizing its capacity to receive pollutants from various

[1] Minimization of Maximum Regret (MMR)
[2] Minimization of Total Regret (MTR)
[3] Charged System Search (CSS)
[4] Dissolved Oxygen (DO)
[5] Waste Load Allocation (WLA)
[6] Load Allocation (LA)

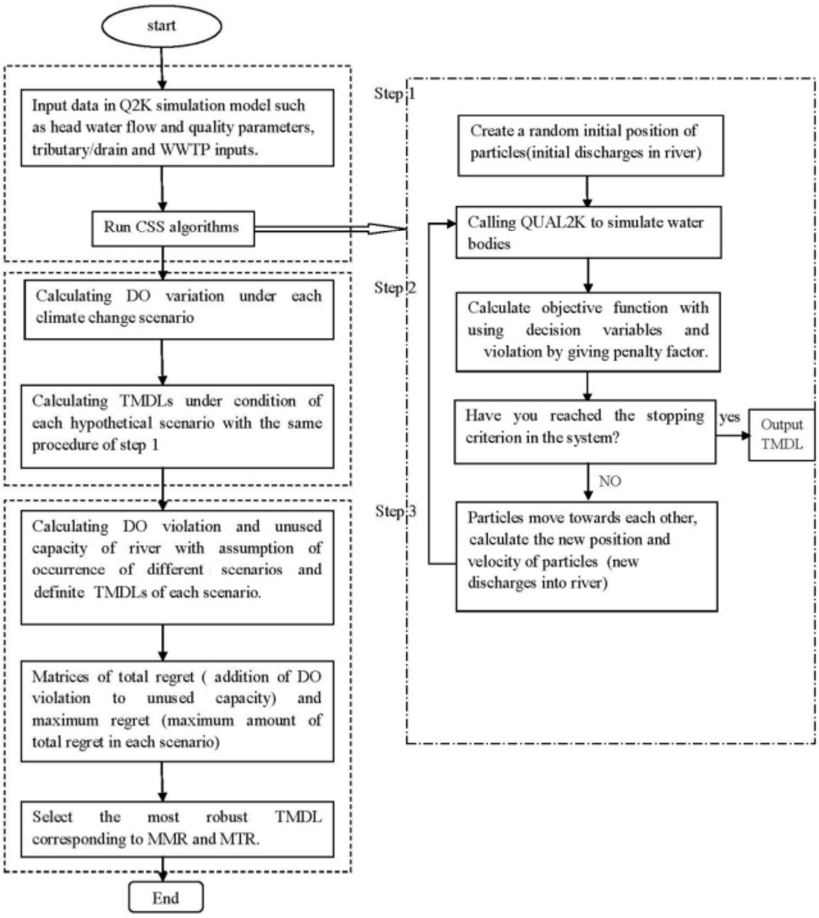

Fig. 1. Flowchart of the proposed methodology

sources. In other words, a TMDL may be recognized as a "pollution budget" designed to restore the health of the polluted water body. Determining a TMDL is difficult for multi-pollutant and a combination of point and distributed pollutant sources because of the fundamentally different nature of the two sources. Nonetheless, the TMDL process is important for improving water quality because it links the development and implementation of control actions to the attainment of water quality standards.

2.2. Charged System Search Algorithm

In this paper, the CSS optimization algorithm is utilized for maximization of total daily load discharged to a running water body under different uncertain conditions. For the pre-evaluation of its capability in handling complex and nonlinear problems, its performance is investigated using three well defined and highly nonlinear benchmark mathematical functions. The CSS algorithm is then applied to load allocation of "New River" from the International Boundary to the outlet at the Salton Sea.

The governing laws of electrostatics in physics and motion from the Newtonian mechanics are basic to the definition of CSS algorithm. CSS is a multi-agent approach, where each agent is a Charged Particle[1]. CPs can attract or repel each other because of their electrical forces. The position of each CP is specified by utilizing the Newtonian mechanics.

Each CP, based on the quality of its solution, has a charge (q_i) equal to

$$q_i = \frac{\text{fit}(i) - \text{fitworst}}{\text{fitbest} - \text{fitworst}} \quad , \quad i = 1,2,...,N \qquad (2)$$

Where

fitbest" and "fitworst" are the best and the worst fitness of all the particles; fit(i)is the fitness of the *(i),* the agent and *(*N) is the total number of CPs. The initial positions of CPs are determined randomly in the search space and the initial velocities are taken as zero (Kaveh and Talatahari, 2010).

[1] Charged Particle (CP)

$$x_{(i,j)}^{(0)} = x_{i,min} + rand(x_{i,max} - x_{i,min}) \quad , \quad i = 1,2,...,N \quad (3)$$

$$v_{(i,j)}^{(0)} = 0 \quad , \quad i = 1,2,...,N \quad (4)$$

Where

$x_{(i,j)}^{(0)}$ and $v_{(i,j)}^{(0)}$ specify the initial value and initial velocity of the i th variable for the jth CP respectively; $X_{i,min}$ and $X_{i,min}$ are the minimum and the maximum allowable values for the i th variable; rand is a random number in the interval [0, 1]; and N is the number of variables.

The magnitude of the force between CPs, which is considered as a charged sphere affecting other CPs, is determined from Coulomb and Gauss's law (Kaveh and Talatahari, 2010)

$$F_j = q_i \sum_{i,i \neq j} \left(\frac{q_i}{a^3} r_{ij}.i_1 + \frac{q_i}{r_{ij}^2}.i_2 \right) p_{ij}(X_i - X_j) \quad \left\langle \begin{array}{l} j = 1,2,...,N \\ i_1 = 1, i_2 = 0 \Leftrightarrow r_{ij} < a \\ i_1 = 0, i_2 = 1 \Leftrightarrow r_{ij} \geq a \end{array} \right. \quad (5)$$

Where
$F_j$is the resultant force acting on the jth CP, and $r_{ij}$is the distance between the two charges as follows

$$r_{ij} = \frac{\| X_i - X_j \|}{\| (X_i + X_j)/2 - X_{best} \| + \varepsilon} \quad (6)$$

In Eq. 6, ε is a small positive number to avoid singularity, X_i, X_j and X_{best} are the positions of the i th, jth, and the best CPs respectively. The probability of moving particle i toward the j(p_{ij}) is defined as

$$p_{ij} = \begin{cases} 1 & \frac{fit(i) - fitbest}{fit(j) - fit(i)} > rand, fit(j) > fit(i) \\ 0 & otherwise \end{cases} \quad (7)$$

$$X_{j,new} = rand_{j1}.k_a.\frac{F_j}{m_j}.\Delta t^2 + rand_{j2}.k_v.V_{j,old}.\Delta t + X_{j,old} \quad (8)$$

$$V_{j,new} = \frac{X_{j,new} - X_{j,old}}{\Delta t} \quad (9)$$

$rand_{j1}$ and $randj_2$ are two random numbers uniformly distributed in the range (0, 1); Δt is the time step and is set to unity, K_a is the acceleration coefficient and K_v is the velocity coefficient. K_a and K_v are control parameters of the exploitation and exploration of the algorithm respectively

$$k_a = \alpha \times (1 + iter / iter_{max}) \quad , \quad k_v = \beta \times (1 - iter / iter_{max}) \quad (10)$$

iter refers to the actual iteration number and $iter_{max}$ is the maximum number of iterations. With this equation, K_v linearly decreases while K_a linearly increases as the number of iterations increases. In this way, the balance between the exploration and the fast rate of convergence is saved.

Replacing for K_a and K_v from (10), Eqs. (8-9) can be rewritten as

$$X_{j,new} = \alpha \times rand_{j1}.(1 + iter/iter_{max}).\sum_{i,i \neq j} \left(\frac{q_i}{a^3} r_{ij}.i_1 + \frac{q_i}{r_{ij}^2}.i_2 \right) p_{ij}(X_i - X_j) + \beta \times rand_{j2}.(1 - iter/iter_{max}).V_{j,old} + X_{j,old} \quad (11)$$

$$V_{j,new} = X_{j,new} - X_{j,old} \quad (12)$$

If each CP moves out of the allowable search space, correct the position according to the following instructions

$$x_{i,j} = \begin{cases} w.p.CMCR & \Rightarrow \text{Select a new value for a variable from CM} \\ & \Rightarrow w.p.(1\text{-}PAR) \text{ do nothing} \\ & \Rightarrow w.p.PAR \text{ choose a neighboring value} \\ w.p.(1\text{-}CMCR) & \Rightarrow \text{select a new value randomly} \end{cases} \quad (13)$$

"w.p." stands for "with the probability"; The Charged Memory Considering Rate[1] is a number between 0 and 1 and sets the rate of choosing a value from the best results which are stored in the Charged Memory[2], and (1−CMCR) sets the rate of randomly choosing one value from the possible range of values. The value (1−PAR) sets the rate of doing nothing, and PAR sets the rate of choosing a value from the neighborhood of the best CP. A flowchart of the CSS algorithm is presented in Fig. 1.

2.3. TMDL simulation –optimization model

In a load allocation problem, the objective is to find a set of discharges which maximize the load without violating water quality standards at the check points. Therefore, mathematically stating, the TMDL development may be defined as (Du et al., 2012)

[1] Charged Memory Considering Rate (CMCR)
[2] Charged Memory (CM)

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$$\text{Maximize} \sum_{j=1}^{Np} \text{Load}_j \tag{14}$$

Subject to:

$$DO_i \geq DO_{standard} \tag{15}$$

Where

NP is the number of dischargers, DO is dissolved oxygen, i and j identify the check points and the dischargers, respectively. The well-known penalized objective function is employed to handle the constraint for eliminating the chance of DO violation at the check points. Therefore, the objective function defined by Eq. 14 was replaced by the penalized objective function to satisfy the constraints set defined by Eq. 15(Du et al., 2012)

$$\text{Maximize} \sum_{j=1}^{Np} \text{Load}_j - \text{Penalty} \tag{16}$$

Determination of the proper value of the penalty and/or penalty coefficient in constraint handling via penalized objective function has remained as a challenging issue. Large penalty coefficients often reduce the exploration by concentrating on limited search area and accelerating the convergence to a premature solution and vice versa. Afshar successfully applied a self-adaptive penalty method which automatically adjusts the value of the penalty parameter toward its desired a priori unknown value (Afshar, 2008). The best value for the penalty increases the chance of obtaining a good solution with minor constraints violation. It supports the evolution process by keeping the search on and around the boundary of the feasible region. In this paper we employed the iterative procedure proposed by Afshar (Afshar, 2008) as

$$\text{Penalty}(t+1) = \text{Penalty}(t) \times \left(\frac{f_{bfs}}{f_{bis}}\right)(1+TCV) \tag{17-a}$$

If a feasible solution is found

$$\text{Penalty}(t+1) = \text{Penalty}(t)(1+TCV) \tag{17-b}$$

Otherwise,

Total Constraint Violation[1] (Eq.18), f_{bfs} and f_{bis} refer to values of the objective functions for the best feasible and non-feasible solutions in the current iteration, respectively. TCV is defined as

$$TCV = \sum_{i=1}^{NC} \text{Deviation}_i \tag{18}$$

where

NC is the number of checkpoints. As presented in Eq.19, the sum of positive deviations from the standard dissolved oxygen is a measure of infeasibilities in any generated trial solution(Du et al., 2012):

$$\text{if } DO_{standard} - DO_i > 0 \Rightarrow \text{Deviation}_i = DO_{standard} - DO_i \tag{19}$$

$$\text{if } DO_{standard} - DO_i \leq 0 \Rightarrow \text{Deviation}_i = 0 \tag{20}$$

To evaluate the DO concentration in each check point, the entire system must be simulated. In this study a full -scale water quality simulation model (QUAL2K) is employed and coupled with the optimizer in a simulation-optimization scheme. QUAL2K river model is distributed by USEPA[2] and it uses one-dimensional systems and steady state flow equations. Simulation of temperature, water quality and hydrological conditions of rivers with point and non- point pollution loads, make it useful enough for rivers.

The full-scale process based QUAL2K simulation model provides a detailed representation of the system which is called to compute the state variables for estimation of the objective function for any trial solution. In this application, the fitness value is calculated as the total daily loads. The mass of daily load in each discharge point forms the set of decision variables. The trial solutions with known values of the decision variables form an input array to the simulation model for calculation of dissolved oxygen concentrations in the check points.

2.4. Application of the Model

2. 4.1. Model Setup

Data from New River in the USA is used to illustrate the application and test the performance of the proposed regret-based approach to TMDL modeling. As shown in the Regional Water Board monthly data collected for 1997-2002, the primary sources of pollutants in the headwater are the untreated or partially treated urban and industrial wastewater discharged to the New River and its tributaries in Mexicali, Mexico. Schematic plan view of the river and distribution of the selected waste discharging points along the river are illustrated in Fig. 2.

[1] Total Constraint Violation (TCV)

[2] United States Environmental Protection Agency (USEPA)

Table 1. Inflow and water quality parameters in the headwater

Parameter	Unit	Value
Stream flow	m^3/s	3.625
Temperature	^0C	30.5
Conductivity	U mhos	5786
Inorganic solid	mg/L	46
Dissolved oxygen	mg/L	5
CBOD slow	mgO_2/L	0.00
CBOD fast	mgO_2/L	0.00
Organic nitrogen	UgN/L	1000
NH_4-nitrogen	UgN/L	1550
NO_3-nitrogen	UgN/L	200
Organic phosphorus	UgP/L	1000
Inorganic phosphorus	UgP/L	1000
Phytoplankton	UgA/L	4
Alkalinity	$mgCaCO_3/L$	233
PH	s.u.	7.82

Discharge and adjusted values of selected water quality parameters at the headwater are presented in Table 1. Discharge and water quality parameters from the selected dischargers along the river are presented in Table 2.

The scenarios selected for this study are considered based on the literature (Ficklin et al., 2009, Rehana and Mujumdar, 2011), IPCC Special Report on Emission Scenarios (SRES) ((IPCC), 2001b) and The Physical Science Basis ((IPCC), 2007). Depending on the greenhouse gas emission scenario, atmospheric CO_2 is expected to increase from the current concentration of 415 ppm to a value between approximately 550 and 970 ppm by the end of the 21st century ((IPCC), 2001a).

The scenarios with the highest projected CO_2 concentrations (A1FI scenario – 970 ppm by 2100) and the lowest (B1 scenario– 550 ppm by 2100) have been selected in this study.

The A1FI scenario assumes a future world of very rapid economic growth, global population that peaks in mid-century and declines, rapid introduction of new and more efficient technologies. The B1 scenario, in contrast, corresponds to a future of low economic growth and fossil fuel independency. Although prediction of rainfall does not show the same changes (increasing or decreasing), we have considered the worst conditions of decreasing as hypothetical scenarios which are presented in Table 3

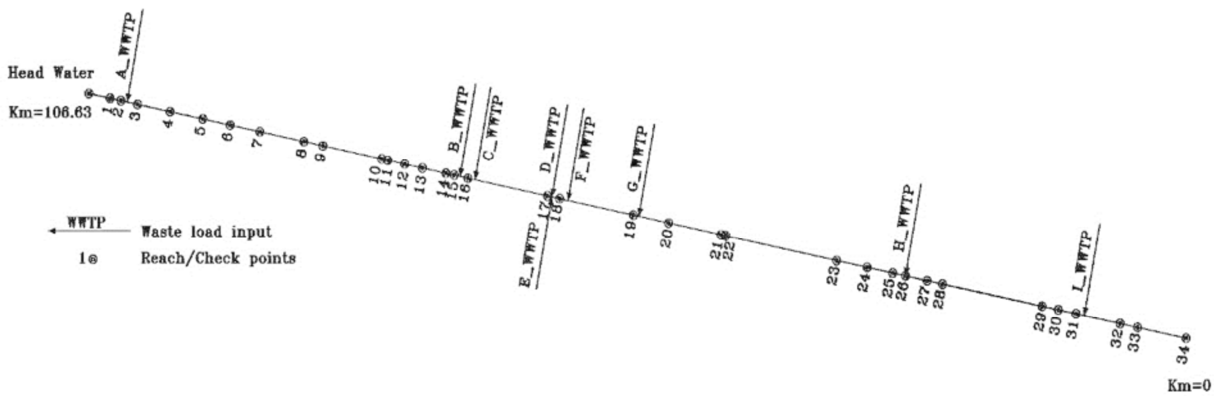

Fig. 2. Illustration of river, waste load inputs, reaches/check points

Table 2. Discharge and water quality parameters from the dischargers along the river reach

Point source/drain flow (dischargers)	Distance from downstream(km)	Average inflow(m3/s)	Average temp(°C)	Average DO (mg/L)	Fast CBOD (mg/L)
A_WWTP(Calexio)	104.93	0.1116	30.83	4.07	29.9
B_WWTP(Seeley)	72.51	0.0057	30	10.1	30.8
C_WWTP(Bullhead)	71.15	1.593	29.65	7.45	2
D_WWTP(Salt Creek)	63.29	1.593	29.65	7.45	2
E_WWTP(Centinela Prison)	63.29	0.0263	30	5	10
F_WWTP(El Centro)	62.37	0.0048	30	5	6.4
G_WWTP(Date Gardens)	54.75	0.0005	30	4.3	8.2
H_WWTP(Brawley)	27.8	0.1665	31.7	3.4	11.2
I_WWTP(Westmoreland)	10.08	0.007	30	4.4	24.4

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Table 3. Six presumed climate change scenarios

S1	• Change in average air temperature = 1.1 ˚C • Change in average precipitation = 0% , • Low emissions (B1)
S2	• Change in average air temperature = 1.1 ˚C • Change in average precipitation = -10%, , • Low emossions (B)1))
S3	• Change in average air temperature = 1.1 ˚C • Change in average precipitation = -20%, • Low emissions (B1)
S4	• Change in average air temperature = 6.6 ˚C • Change in average precipitation = 0% • High emissions (A1F1)
S5	• Change in average air temperature = 6.6 ˚C • Change in average precipitation = -10% • High emissions , A1F1
S6	• Change in average air temperature = 6.6 ˚C • Change in average precipitation = -20% • High emissions , A1F1

(0%, -10%, and -20%). Notice that change in precipitation is used to modify the change in river flow.

To establish a relation between air temperature and water temperature which is required to apply it in QUL2K model, a linear regression relationship should be employed using daily timescale data of water temperature (for example from USGS gage) and weather data. The following regression equation is assumed for this project

$$T_w = 0.83T_a + 2.73 \quad (21)$$

The validation and verification of developed simulation-optimization model is reported in Faraji et al. (Faraji et al., 2015) which reported complete validation of the developed model.

Table 3 assumes six different conditions due to climate change. It is also assumed that occurrence of any of those scenarios is uncertain and none of them has any priority over the others. In other words, under any scenario, an optimum loading can be defined which optimizes the assigned objective function. Those optimal solutions will certainly differ from each other. The challenge to water resource planners is to find a robust decision in such an uncertain environment. If, for example, with a cautious or pessimistic prospect, waste load is allocated based on scenario 6, occurrence of other climate scenarios will result in unused capacity of river, which may impose economic, industrial and environmental costs. With a risk taking or optimistic prospect, on the other side, if load is allocated based on scenario 1 or even the base line condition, occurrence of other climate scenarios may lead to DO violation along the river, causing economic, industrial and environmental costs.

2.4.2. Regret-based optimum waste discharge permit

In application of regret methods, the uncertainties are implicitly considered by defining numbers of scenarios which assign probable values to uncertain parameters. Discrete scenarios and interval scenarios are the two most common ones. In discrete scenarios each member of the scenario has a precise and discrete value. In this study, regret for planners might be explained with unused allowable capacity of river and violation from water quality standards and TMDL regulations addressed as DO deficit at all checkpoints along the river.

Let $Z(x,s)$ be the total maximum daily load under climate change scenario s and solution x where x is a solution that consists of vector of loads allocated to each discharger. In this definition $x \in X$ and $s \in S$ in which X is decision space and S defines the set of all possible climate change scenarios. For scenario $s \in S$, the regret for any solution $x \in X$ is defined as

$$R(x,s) = Z(x,s) - Z(x^*,s) \quad (22)$$

Where

$Z(x^*,s)$ is the total maximum daily load with optimal solution x^* under scenario s. The optimal solution x^* can be obtained by running the optimization model to maximize the total daily load subject to the imposed constraints. Therefore, the MMR model aims to minimize the maximum values of the $R(x,s)$ over the entire scenarios

$$MMRegret = Min\{MaxR(x,s)\} \quad (23)$$

Using the same concept and approach, the total regret over the entire scenarios might be minimized. In this case, the minimized total regret (MTR) may be defined as

$$MTRegret = Min\Sigma_s R(x,s) \tag{24}$$

Outcome matrices for Unused Capacity[1] and Dissolved Oxygen Violation[2] are calculated by allocating waste loads (X_s) driven from simulation-optimization model of previous step for base condition and 6 presumed climate change scenarios using Qual2K model. After calculating the total daily load allocation for the baseline condition, DO variations are calculated with the assumption that discharge permits are allocated under the base condition whereas another climate change scenario would happen. In this way, the DOV and UC of river matrices for each scenario can be determined. In this paper pay-off factor (which determines economic, industrial and environmental costs of DO violation or unused capacity of river in future load allocation) was assumed in first option as equal and was not considered in regret matrices and in second option it was assumed.

For developing regret matrices, first the least outcomes for each climate change scenario should be determined and then subtract the outcomes of each load allocation (X_s) under this specific climate change scenario from the least outcomes (Colombo and Byer, 2012). After determining maximum regret of each load allocation (X_s), the minimum number would be chosen for making decision based on MMR criteria. MTR is simply determined first by adding regret of each load allocation (X_s) and then choosing minimum number. Finally, the best allocation with considering regret in future would be chosen by authorities and decision makers.

3. Results and discussion

As any other stochastic optimization algorithm, CSS is not expected to end up with the same solution for different computer runs. This is basically because of stochastic search of the algorithm in the entire solution space. Therefore, it is a common practice to conduct a few independent computer runs with the same stopping criteria to show how diverse the results could be. To test the performance of the proposed model, 10 independent runs for the baseline condition with minimum allowable DO of 5 mg/L is conducted. Results for the baseline condition and the limiting value of 5 mg/L of DO for 10 different runs are presented in Fig. 3. As illustrated, the allocated TMDL ranges from 49483.1 to 51917.2 Kg of CBOD/day with average and standard deviation of 50690 and 979, respectively. Small standard deviation of the 10 independent runs is an indication that the algorithm is

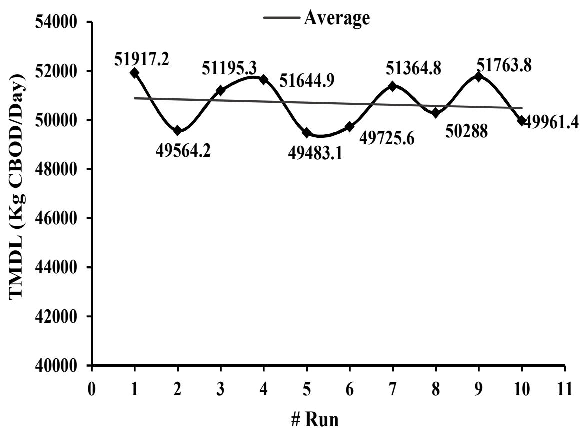

Fig. 3. Result of different runs under baseline condition

producing good-near optimal results with different searches in the solution space. The relatively small standard deviation may justify its robustness and satisfactory performance.

In the next step, initial loads are reallocated under climate condition of each assumed scenario with the simulation-optimization CSS model based on TMDL. Head water temperature is evaluated using regression equation 21 for different air temperature in each scenario. For fair comparison of consequences under different climate scenarios, the same head water condition was considered in each scenario (except water flow and temperature). We assumed that the mass of input contaminants in head water remains unchanged from one scenario to the others. Resulted TMDL for different scenarios is presented in Table 4.

Table 4 presents the total daily CBOD that can be discharged to the river at different receiving points without violating the standard DO, as set to 5 mg/L in this study. It shows that under existing climate condition, the river may receive an additional 51916 kg CBOD without causing any DO deficit, provided that the headwater characteristics remain unchanged. Table 4 reveals that as temperature increases and/or the river flow decreases, the total maximum daily load declines. In other words, as expected, any decrease in river discharge and/or increase in air temperature would reduce the system's capacity in receiving waste loads. This reduction is more significant for scenarios number 5 and 6, where increase in air temperature and/or decrease in stream flow are more pronounced. Now the main question is how to determine and allocate the TMDL between the potential dischargers, considering the uncertainties in future conditions. As a bit of information, under scenario number 6 and in comparison, to the existing condition, the capacity of the river for receiving additional CBOD would reduce from 51916 to 38557 Kg CBOD/day.

As stated earlier, the regret method intends to allocate the waste loads to different dischargers to minimize

[1] Unused Capacity (UC)
[2] Dissolved Oxygen Violation (DOV)

regrets associated with occurrence of any other condition. Table 5 shows the unused (or overused) capacity of the river for receiving CBOD per day for any proposed waste allocation option if any assumed climate change scenario occurs.

As presented in Table 5, if the authorities allocate the TMDL according to scenario 4 (Table 3) and the same condition occurs in the future, there would no unused (or overused) capacity with zero deficit. However, under this loading condition, occurrence of scenarios 5 or 2 would end up with overused capacity of 834 (-834 Kg CBOD/day) and unused capacity of 4068 Kg/day, respectively. The overused capacity will certainly lead to violation from the standards, causing DO deficits at some of the checkpoints. As another example, if the authorities choose to follow the waste load allocation based on climate condition for scenario $X_{(s=3)}$, there would again be no unused or overused capacity. Occurrence of baseline condition (existing condition), however, would leave significant DO deficit along the river with overusing the river capacity by 2816 Kg CBOD per day. In other words, under this circumstance, to reduce the DO deficit to zero along the river at all checkpoints, the authorities must reduce the allocated CBOD load by 2816 Kg/day and reallocate the load accordingly. For developing regret matrices, both DO violation matric and unused capacity matric must be employed and integrated.

Results presented in Table 6 indicate that, if the baseline condition is excluded from the possible solution strategies, the minimum of maximum regret is expected from adapting waste load allocation based on scenario number 3 from Table 3. Although it cannot be generalized, the minimization of total regret is also associated with adaptation of scenario number 3 with minimum of total regret of 8927 Kg CBOD/day. The results indicate that, if scenario number 3 is chosen for initial waste load allocation, there would be a maximum regret of 2816 Kg. CBOD/day as summation of unused and/or overused capacity along the river. Occurrence of other scenarios would result in smaller regret as compared to 2816 Kg CBOD/day. The same conclusion can be drawn for the minimization of total regret.

Table 4. Optimal TMDLs and allocated waste to different dischargers under different climate change scenarios (Kg CBOD/Day)

Point source waste flow	Baseline condition	Scenario1 (Table 3)	Scenario 2 (Table 3)	Scenario3 (Table 3)	Scenario4 (Table 3)	Scenario5 (Table 3)	Scenario6 (Table 3)
A_WWTP	1	<1	<1	<1	<1	<1	<1
B_WWTP	2032	1820	1820	1818	1817	1816	1816
C_WWTP	83	52	69	77	47	65	69
D_WWTP	233	186	98	83	49	29	21
E_WWTP	5525	53421	4704	4049	3912	3428	2896
F_WWTP	1600	1508	1534	1527	1534	1531	1530
G_WWTP	160	158	159	159	159	159	159
H_WWTP	39809	39403	37724	36755	32144	31183	29830
I_WWTP	2474	2237	2237	2236	2237	2237	2236
Xs:TMDL (KgCBOD/Day)	51916	50706	48345	46704	41899	40448	38557

Table 5. Unused or overused capacity (Kg CBOD/Day) resulted from different loadings in the river under assumed climate change scenarios

Waste load allocation option	Baseline condition	Scenario 1 (Table 1)	Scenario 2 (Table 1)	Scenario 3 (Table 1)	Scenario 4 (Table 1)	Scenario 5 (Table 1)	Scenario 6 (Table 1)
X(s=0)	0	-2607	-3337	-4381	-4694	-5319	-6362
X(s=1)	6989	0	-1210	-2263	-2712	-3442	-4589
X(s=2)	8553	730	0	-1147	-1773	-2503	-3650
X(s=3)	10326	2086	1356	0	-1001	-1668	-2816
X(s=4)	13080	4798	4068	2326	0	-834	-1982
X(s=5)	14498	6258	5528	3807	1147	0	-1251
X(s=6)	16376	8032	7302	5653	2816	1669	0

Table 6. Regret matric under different strategy and loading conditions

Waste load allocation	Total regret	Maximum regret	Total regret	Maximum regret
Options	First Strategy	First Strategy	Second Strategy	Second Strategy
$X_{(s=0)}$	26700	**6362**	26700	6362
$X_{(s=1)}$	21205	6989	14216	4589
$X_{(s=2)}$	**18356**	8553	9803	3650
$X_{(s=3)}$	19253	10326	**8927**	**2816**
$X_{(s=4)}$	27088	13080	14008	4798
$X_{(s=5)}$	32489	14498	17991	6258
$X_{(s=6)}$	41848	16376	25472	8032
MinMax	**18356**	**6362**	**8927**	**2816**

The results show that, under second strategy where the existing condition is excluded, the total regret for all strategies in waste load allocation is presented in the third column of Table 6. It shows that the minimum of total regret occurs if scenario number three is adapted for the initial waste load allocation. In this case, the total regret would be equal to 8927 Kg CBOD/day. Again, if any other scenario is adapted, the total regret would certainly exceed that of scenario number three. As an example, if scenario number one or 5 is selected for primary waste load allocation, then the total regrets would be equal to 14498 and 17991, respectively.

If the baseline condition is included in the list of possible alternatives, then the final results for minimized maximum and minimized total regret may change. In fact, under this circumstance, the minimum of maximum regret supports the waste load allocation based on the existing condition. In this case, the minimum of maximum regret would be equal to 6362 Kg CBOD/day which refers to the regret associated with occurrence of scenario number 6. Again, if for example, the scenario number 4 is adapted for waste load allocation, then much higher regret would be expected (column 2 of Table 6). Under this circumstance, the total regret would be equal to 18356 Kg CBOD/day which is the smallest regret compared to other feasible solutions.

4. Conclusions

Dynamic change in climate and watershed morphology would affect water quantity and quality, though its precise effects are still highly uncertain. Authorities should design a robust approach for reallocating waste loads to the receiving bodies should any changes on climate occur. To comply with the possible changes, this paper proposed a regret-based modeling approach which maximized the total dischargeable load while minimizing the regret associated with the selected alternative. Implementing regret-based decision making (MTR and MMR) for analysis of uncertainties in climate condition and its impact on the load reallocation was used as a cautious method for future planning. It was illustrated that the uncertainties in climate change may be included in the decision-making process through regret analysis approach. It was shown that by minimizing the maximum or total regret a relatively robust plan may be developed. Realizing the continuous nature of the decision space in load allocation and TMDL calculation problem, the CSS algorithm performed quite satisfactorily and was recommended for similar studies.

References

Afshar, A. & Amiri. H 2010. A min-max regret approach to unbalanced bidding in construction. *Civil Engineering,* 14**,** 653-661.

Afshar, A. & Najafi, E. 2014. Consequence management of chemical intrusion in water distribution networks under inexact scenarios. *Hydroinformatics,* 16**,** 178-188.

Afshar, M. H. 2008. Penalty adapting ant algorithm: application to pipe network optimization. *Engineering Optimization,* 40**,** 969-987.

Aissi, H., Bazgan, C. & Venderpooten, D. 2009. Min-max and minmax regret versions of some combinatorial optimization problems: a survey. *European Journal of Operational Research,* 197**,** 427-438.

Asadieh, B. & Afshar, A. 2019. Optimization of water-supply and hydropower reservoir operation using the charged system search algorithm. *Journal of Hydrology,* 6**,** 1-16.

Byer, P. H., Lalani, M. J. & Yeomans, J. S. 2009. Addressing and communicating climate change and its uncertainties in project environmental impact assessments. *Environmental Assessment Policy and Management,* 11**,** 29-50.

Chang, N. & Davila, E. 2007. Minimax regret optimization analysis for a regional solid waste management system. *Waste Management,* 27**,** 820-832.

Chen, W. W., Herr, J., Ziemelis, L., Goldstein, R. A. & Olmsted, L. 1999. Decision support system for total maximum daily load. *Journal of Environmental Engineering,* 125**,** 653-659.

Colombo, A. F. & Byer, P. H. 2012. Adaptation, flexibility and project decision-making with climate change uncertainties. *Impact Assessment and Project Appraisal,* 30**,** 229-241.

Dilks, D. & Freedman, P. 2004. Improved consideration of the margin of safety in total maximum daily load development. *Environmental Engineering,* 130**,** 690-694.

Du, P., Li, Y. P. & Huang, G. H. 2012. Agricultural water management under uncertainty using minimax relative regret analysis method. *Journal of Irrigation and Drainage Engineering,* 138**,** 1033-1045.

Faraji, E., Afshar, A. & Feizi, F. 2015. Load allocatin with total maximum daily load (TMDL) approach with charged system search algorithm. *Journal of Water and Wastewater,* 26**,** 35-47. (In Persian)

Ficklin, D. L., Luo, Y., Luedeling, E. & Zhang, M. 2009. Climate change sensitivity assessment of a highly agricultural watershed using SWAT. *Journal of Hydrology,* 374**,** 16-29.

Hof, A. F., Van Vuuren, D. P. & Den Elzen, M. G. 2010. A quantitative minimax regret approach to climate change: Does discounting still matter? *Ecological Economics,* 70**,** 43-51.

(IPCC), I. P. O. C. C. 2001a. Climate change 2001: impacts, adaptation, and vulnerability contribution of working group II to the third assessment report of the intergovernmental panel on climate change.

(IPCC), I. P. O. C. C. 2001b. Climate change 2001: the scientific basis contribution of working group I to the third assessment report of the intergovernmental panel on climate change.

(IPCC), I. P. O. C. C. 2007. Climate change 2007: the physical science basis contribution of working group I to the fourth assessment report of the intergovernmental panel on climate change.

Jia, Y. & Culver, T. B. 2006. Robust optimization for total maximum daily load allocations. *Water Resource Research,* 42**,** 1-10.

Kaveh, A. & Talatahari, S. 2010. A novel heuristic optimization method: charged system search. *ActaMechanica,* 213**,** 267-289.

Kunreuther, H., HEAL, G., Allen, M., Edenhofer, O., B. Field, C. & Yohe, G. 2013. Risk management and climate change. *Nature Climate Change,* 3**,** 447-450.

Loulou, R. & Kanudia, A. 1999. Minimax regret strategies for greenhouse gas abatement: methodology and application. *Operations Research Letters,,* 25**,** 219-230.

Maass, A., Hufschmidt, M. M., Dorfam, R., Thomas, H. A., Margling S. A. & Maskew Fair, G. 1962. *Design of Water-Resource Systems,* Cambridge, Harvard University Press.

Mausser, H. E. & Laguna, M. 1998. A new mixed integer formulation for the maximum regret problem. *International Transactions in Operational Research,* 5**,** 389-403.

Mirchi, A. & Watkins, D. J. 2013. A systems approach to holistic total maximum daily load policy: case of Lake Allegan, Michigan. *Journal of Water Resources Planning and Management,* 139**,** 544-553.

Poorsepahy-Samian, H., Kerachian, R. & Nikoo, M. R. 2012. Water and pollution discharge permit allocation to agricultural zones: application of game theory and min-max regret analysis. *Water Resources Management,* 26**,** 4241-4257.

Rehana, S. & Mujumdar, P. P. 2011. River water quality response under hypothetical climate change scenarios in Tunga-Bhadra river, India. *Hydrological Processes,* 25**,** 3373-3386.

Taher, I. A. & Culver, T. B. 2007. Assessing the impact of BMP performance uncertainties in TMDL allocation. *EWRI, World Water and Environmental Resources Congress.*

Taher, I. A. & Culver, T. B. 2008. Cost optimization for robust optimal TMDL allocation. *ASCE, World Environmental and Water Resources Congress.*

USEPA, 2005. TMDL Model Evaluation and Research. U.S. Environmental Protection Agency.

Willows, R. I. & Connell, R. K. 2003. Climate adaptation: risk, uncertainty and decision-making, UKCIP technical report. Oxford, UK.