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Multi-Objective Hydraulic Optimization of Diversion Dam's Cut-Off

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Abstract The seepage flow beneath a hydraulic structure is formed by the hydraulic head difference between the upstream and downstream sides. Cut-off walls are often applied, as an expedience, to reduce the seepage flow through the foundation of diversion dams and to enhance the efficiency of these dams. In this research, perhaps for the first time, a novel methodology is propounded to assess the optimum characteristics of cut-off walls in diversion dams in order to ameliorate hydraulic interactions between the diversion dam foundation and the cut-off walls behavior, also their construction cost is minimized. The results are used to train and validate the Multi-Layer Perceptron (MLP) simulation model. Then MLP, as a meta-model for simulation of the hydraulic behavior of cut-off walls, is coupled with a robust multi-objective optimization algorithm, Non-dominated Sorting Genetic Algorithm-II (NSGA-II), to create a trade-off between the intended goals. Finally, Preference Ranking Organization METHod for Enrichment Evaluation (PROMETHEE) decision making model and Nash-Harsanyi bargaining model are utilized to find the compromise design optimal solution on the trade-off curve. Results demonstrate that the best agreed-upon design optimal solution using PROMETHEE and Nash-Harsanyi bargaining models can be considered as (10, 3.84, 32) meters and (2.47, 10, 29.22) meters for optimum depth of the upstream and downstream cut-off walls and the optimum distance between them, respectively.

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1 Introduction

Foundations of all hydraulic structures are more significant than other parts in design and behavior analysis topics since any existing problem in them causes the whole structure to be non-efficient or even gets destroyed (Al-Delewy et al. 2006). Moreover, in the first phase of dam design, many important factors should be taken into consideration such as accurate selection of the geotechnical parameters, stability analysis of dam body, an acceptable estimation of seepage flow through the dam and suitable primary approximation of the dam dimensions, which requires approaching the multi-objective optimization models, while single-objective ones are not efficient enough to prepare a comprehensive interaction between different objectives of hydraulic design of dams (Mehrdad et al. 2006). Also, it is necessary to understand and meet the expectations of various viewpoints of all involved stakeholders in dam design projects and manage any inconsistencies and conflicts.

So far, many researches have been conducted to investigate seepage flow behavior through dams and their foundations by numerical modeling (Harr 1962). They only change the location of seepage control equipment to monitor its effects on seepage flow behavior. Azizi et al. (2012) assessed the effects of making changes in locations of weep holes and cut-off walls on uplift pressure. They simulated Yusufkand Mahabad diversion dam in Iran using Seep/W module in Geostudio software. Conclusions state that the upstream cut-off wall reduced the uplift force about 63% comparing with the state without seepage control equipment and likewise decrease the exit gradient about 79% (Azizi et al. 2012). A framework of integrating the simulation of seepage flow through the foundation of hydraulic structures considering effects of seepage control devices on minimizing uplift force, seepage flow discharge and exit gradient at toe of dams is presented in Sabbagh-Yazdi and Bayat (2006), Chen et al. (2008), Ghobadian and Khodaei (2009), Abdul Kareem Esmat (2011), Obead (2013).

A few researches have been carried out to optimize the characteristics of seepage control equipment. Al-Suhaili and Karim (2014) coupled models of Genetic Algorithm and Artificial Neural Network to find the optimum depth of upstream and downstream cut-off walls, length of the floor and the downstream protection required for hydraulic structures. They used a single objective optimization model to minimize cost function, and uplift pressure and exit gradient were only used as safety factors in form of constraints of the optimization model in their study. But, in the present study, a multi-objective optimization model is prepared in which horizontal and vertical exit gradient and uplift pressure are used as objectives of the optimization model as well as cost and seepage flow discharge. Also, Al-Suhaili and Karim did not utilize any decision making or bargaining models in order to find the compromise optimal solution among various choices for decision makers. Some of other researches about optimization of seepage control devices are: 1- Studying the effects of the optimum location of vertical grout curtain on reduction of seepage flow rate and velocity under the hydraulic structures, (Sedghi-Asl et al. 2005); 2- Investigating the optimum design of seepage control devices of a hypothetical case study using Lagrange-multiplier method without directly utilizing exit gradient and uplift pressure as objectives of the optimization and without considering conflicting interests of stakeholders, (Al-Delewy et al. 2006); 3- Determining the optimal depth of concrete cut-off walls under dams without applying any optimization method, (Yan 2008).

To the best of the authors' knowledge, literature of the optimal design of cut-off wall characteristics lacks a multi-objective simulation-optimization approach using decision making and bargaining models to determine the compromise optimal design parameters considering various standpoints of stakeholders. Accordingly, in this study, a novel methodology is presented, which proposes a multi-objective optimization model to determine the optimal depth of upstream and downstream cut-off walls of diversion dam as well as the optimum distance between them regarding features of Yusufkand Mahabad diversion dam as the case study. The multi-objective optimization algorithm, Non-dominated Sorting Genetic Algorithm-II (NSGA-II), is coupled with Multi-Layer Perceptron (MLP) neural network models, as meta-models, to simulate the hydraulic behavior of cut-off walls under diversion dams by minimizing seepage flow discharge, uplift force, horizontal and vertical exit gradient and construction cost as objectives of the optimization model. Then, Pareto-optimal solutions are obtained from the NSGA-II multi-objective optimization model and the best solution is determined using Preference Ranking Organization METHod for Enrichment Evaluation (PROMETHEE) model and Nash-Harsanyi bargaining model, separately.

2 Methodology

This study works towards developing a multi-objective optimization model to specify the characteristics of cut-off walls of a diversion dam in order to find the underlying design objectives. The important characteristics of cut-off walls under a diversion dam are their depth and the distance between them. It is believed that the upstream cut-off wall decreases the amount of both uplift pressure and exit gradient, while the reduction rate of the uplift pressure is more than the other one. On the other hand, the downstream cut-off wall has definite effect on reducing exit gradient at toe of dam. Increasing the depth of downstream cut-off wall results in significant reduction of exit gradient at downstream face of the dam and causes the uplift pressure to increase simultaneously (Al-Suhaili and Karim 2014). According to these, in this research study, the optimal depth of the upstream and downstream cut-off walls and also the optimum distance between them are required to be designated in order to keep the exit gradient and uplift force at their minimum states. Fig. 1 depicts the proposed multi-objective optimization methodology to designate the optimum characteristics of cut-off walls.

At first, essential information and data required for design of cut-off walls under the diversion dam are gathered and the seepage model of Finite Elements Method (FEM) in Seep/W module of Geostudio software is applied for various design parameters of cut-off walls, namely, depth of both cut-off walls and distance between them. In the second step, the MLP neural network models are trained and validated, as meta-models, to determine the optimal features of cut-off walls when the objectives, i.e., total cost of cut-off appliance and hydraulic properties of the seepage flow through the foundation, are simultaneously considered. Then, the meta-model is connected to a well-organized multi-objective optimization algorithm, NSGA-II, (Deb et al. 2002) to determine the optimal features of cut-off walls considering their hydraulic behavior. Details of utilizing the MLP neural network models and the NSGA-II multi-objective optimization model of cut-off walls will be stated in section 2.1. Ultimately, in the last step, Nash-Harsanyi bargaining model and PROMETHEE decision making model are used to select the compromise non-dominated solution among the available Pareto-optimal solutions regarding hydraulic criteria as well as stakeholders' viewpoints. In the following subsections, more details of each stage are presented.

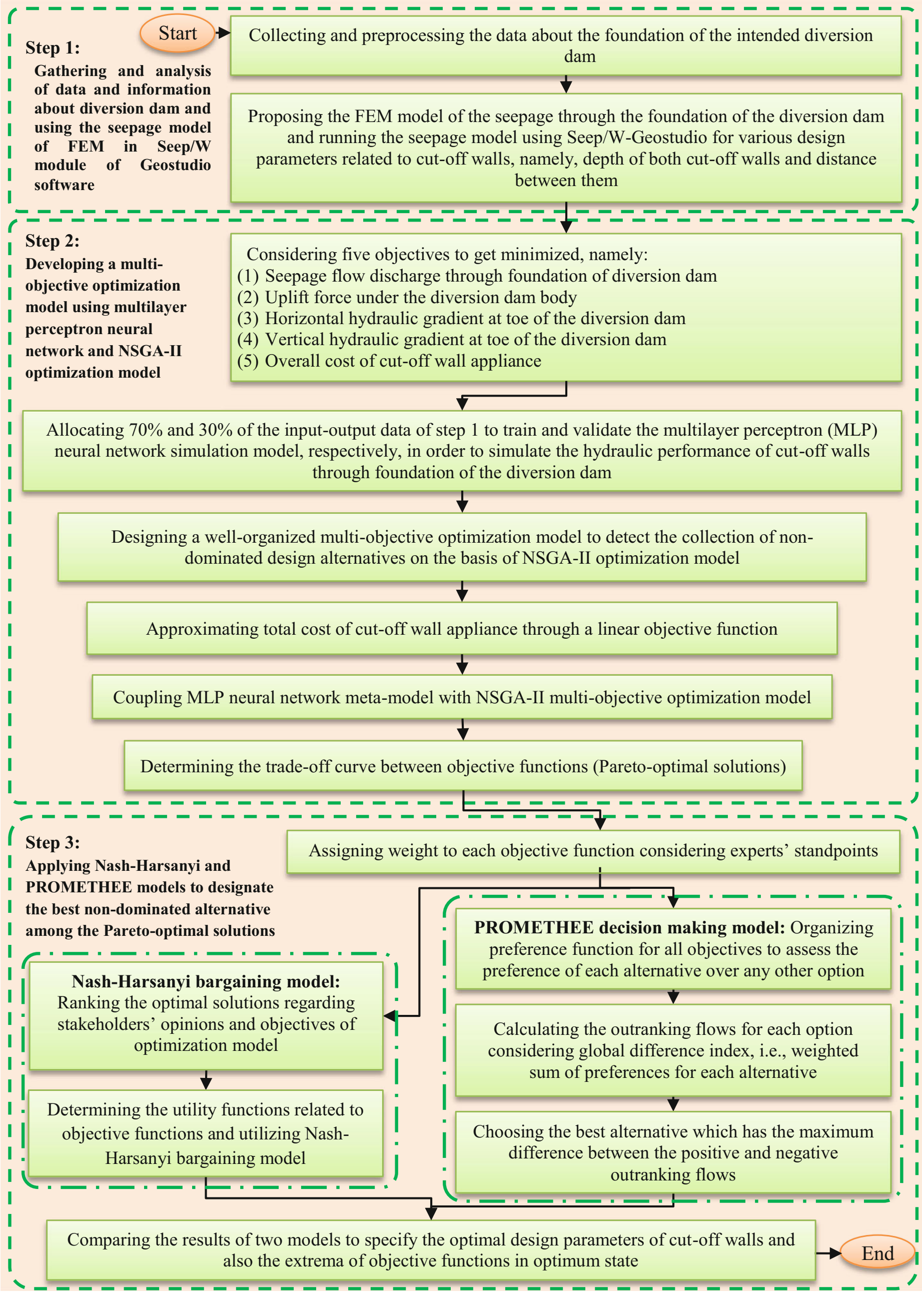


Fig. 1 Framework of the proposed methodology for optimal design of cut-off walls features

2.1 NSGA-II Multi-Objective Optimization Model

In order to enhance the efficiency of diversion dams, some effective strategies are required for considering influential conditions on optimal design of cut-off walls under these dams, which leads to their best hydraulic performance. Flow seepage through diversion dam foundation is not an unexpected event and is manifestly due to the difference between water level at the upstream and downstream of dam body. Seepage flow under diversion dams can be measured and analyzed through three main categories, namely, uplift force, seepage flow discharge and the exit gradient at the toe of the dam.

Furthermore, long-term performance of diversion dams is agreed upon by all stakeholders. In the present study, there are two stakeholders. First, the main contractor who is responsible for executing the project complying with hydraulic standards such as minimizing values of uplift force, seepage flow discharge and exit gradient at toe of the diversion dam. The second stakeholder is construction employer who tends to minimize overall cost of the project. Accordingly, this research study tries to create a reasonable trade-off between these objectives.

The MLP neural network meta-models were connected to the NSGA-II algorithm to determine the optimum values for decision variables as a trade-off curve to be utilized in designating the compromise optimal solution. The MLP neural network model has been used in various research fields of environment (Ostad-Ali-Askari et al. 2017), hydraulic structures (Nikoo et al. 2015), hydrology (Azzellino et al. 2015) and other water-related topics (Zangooei et al. 2016; Alizadeh and Nikoo 2018). Details of using MLP neural network as a meta-model are explained in Online Resource (Explanation S1). The formulated objectives of the proposed multi-objective optimization model related to cut-off walls under a diversion dam are presented as follows:

$$\mathit{Minimize} \quad \mathrm{h}_1 = Q = f(x_1, x_2, x_3) \tag{1}$$

$$\mathit{Minimize} \quad \mathrm{h}_2 = U_p = g(x_1, x_2, x_3) \tag{2}$$

$$\mathit{Minimize} \quad \mathrm{h}_3 = i_x = h(x_1, x_2, x_3) \tag{3}$$

$$\mathit{Minimize} \quad \mathrm{h}_4 = i_y = k(x_1, x_2, x_3) \tag{4}$$

$$\mathrm{Minimize} \quad \mathrm{h}_5 = OC = z(x_1, x_2) \tag{5}$$

$$x_l \le x_i \le x_u \quad \forall i = 1, 2, 3 \tag{6}$$

Where $h_i \,\forall\, i = 1, 2, \ldots, 5$ are objectives of optimization, i.e., the seepage flow discharge through the diversion dam foundation (Q, CMS), uplift force (U_p, KN), horizontal exit gradient (i_x), vertical exit gradient (i_y), and overall cost of applying cut-off walls (OC, \$), respectively. Where x_i refers to the i^{th} decision variable, $i = 1$ to $i = 3$ for the depth of upstream cut-off wall (x_l, m), depth of downstream cut-off wall (x_2, m) and the distance between them (x_3, m), respectively. $f(x_1, x_2, x_3)$, $g(x_1, x_2, x_3)$, $h(x_1, x_2, x_3)$, $k(x_1, x_2, x_3)$ are the non-linear meta-models to estimate the first four objectives of optimization, as functions of design decision variables which are estimated using trained MLP neural network. $z(x_1, x_2)$ is the overall cost which is used as the cost objective in Genetic Algorithm optimization model and is estimated using a multi-variable linear regression. x_l and x_u refer to the lower and the upper values of design decision variables.

It should be noted that the algorithms of MLP neural network models and multi-objective optimization model are programmed using MATLAB® program. In NSGA-II multi-objective optimization algorithm, the maximum number of generation as well as crossover and mutation rates are 100, 0.8 and 0.2, respectively, which are set on the basis of trial-and-error and expert standpoint. Besides, the population size has been stated to be nearly 10 times more than the number of decision variables. Details for implementing NSGA-II multi-objective optimization model can be found in Bin et al. (2010) and Honar et al. (2018).

2.2 Multi-Criteria Decision Making Models

Today, decision making problems are applicable in different branches of science especially engineering disciplines (Nikoo et al. 2015). Multi-criteria decision making models are suitable as solutions to the problems defined with a choice among alternatives. Various researches have been successfully done in different fields considering decision making models such as water resources management (Malekmohammadi et al. 2011; Hadipour et al. 2016), environmental problems (Gregory et al. 2012; Opricovic and Miloradov 2016) and energy management (Pohekar and Ramachandran 2004; Kaya and Kahraman 2011). The PROMETHEE model is one of the decision support system models with a revolutionary effect on decision making problems which has been promulgated in the early 1980s by Brans and others (Brans et al. 1984; Zhang et al. 2009). This technique is easy to use and its level of complexity is low (Cavallaro 2005). PROMETHEE decision making model can present both complete and partial rankings of the actions, and it is appropriate for intricate problems particularly those with several multi-criteria containing many perceptions with long-term impact decisions (Tuzkaya et al. 2008). The basic principles of the PROMETHEE models are explained in Online Resource (Explanation S2).

2.3 Nash-Harsanyi Bargaining Model

Decision making process is usually fraught with difficulties due to the various opinions and priorities of decision makers. Since the n-person decision problems seem to be unsolvable, disagreements and conflicting viewpoints should be considered simultaneously in order to satisfy the decision makers with various attitudes.

Nash-Harsanyi or asymmetric Nash bargaining model is a solution concept in cooperative game theory in which players' preferences (presented by utility functions) are explicitly considered in addition to disagreement points and individual risk taking attitudes (Jafarzadegan et al. 2013). In general form of the Nash model, f_i is supposed to be the utility function of the decision maker i, $\overline{d} = \{d_1, d_2, \ldots, d_n\}$ is the vector of disagreement points and n is the number of decision makers in decision making environment named X. So, the target conditions would be as follows:

$$H = \{u_i = f_i(x), x \in X\} \tag{7}$$

Nash suggested that for convex, closed and bounded utility functions, a unique solution, $(\varphi(H, d))$, satisfies a specified set of intended conditions which can be acquired as solution to the following optimization problem which is called Nash product function (Nash 1950; Harsanyi and Selten 1972; Kerachian and Karamouz 2007):

$$\text{Maximize} \ \ (f_1(x_1)-d_1)^{w_1}(f_2(x_2)-d_2)^{w_2}\ldots(f_n-d_n)^{w_n} \tag{8}$$

$$\text{Subject to} : f_1 \geq d_i \quad \forall i = 1, 2\ldots., n \tag{9}$$

$$f = (f_1, .., f_n) \in H \tag{10}$$

Where w_1, w_2, …, w_n are weights assigned to objectives of optimization in order to express the relative power of decision makers. This problem is known as Nash-Harsanyi (asymmetric) bargaining model. More details for implementing Nash-Harsanyi bargaining model can be found in Kerachian and Karamouz (2007).

2.4 Seepage Simulation by the Finite Elements Method

As mentioned before, model of the intended diversion dam was simulated by Seep/W module of Geostudio software considering the simulation model of the dam body and foundation of Yusufkand Mahabad diversion dam in research study of Azizi et al. (2012).

Thus, in this study, two cut-off walls are added to the simulation model of Yusufkand dam in Azizi et al. (2012) research, one in upstream part of dam body and the other one in downstream, to investigate the variations of seepage flow discharge through foundation, uplift force and exit gradient at toe of dam due to changes of cut-off walls' depth and distance between them. Then, a novel methodology is presented to propose a multi-objective simulation-optimization model to determine the optimal depth of two cut-off walls under diversion dam and optimum distance between them while seepage flow discharge, uplift force and exit gradient are at their minimum state.

The most critical case in simulation occurs when the water level difference between upstream and downstream of a diversion dam equals to the maximum possible amount (Al-Suhaili and Karim 2014). Accordingly, the maximum critical condition has also been considered through numerical simulation of the dam in order to have reliable results, i.e., assigning the maximum amount of 6 m to water level in upstream while the downstream level is set to zero.

In accordance with geologic studies related to Yusufkand diversion dam site, permeability and thickness of foundation layers of this dam is presented in Table S2 (Online Resource) (Azizi et al. 2012). Also, validity of seepage modeling through Seep/W module of Geostudio software is explained in Online Resource (Online Resource, Explanation S3).

It should be noted that in this research, the seepage flow through dam foundation is modeled using FEM. The aforementioned model is then executed repeatedly for the two 50 cm thick cut-off walls with different amounts of depth and also various possible quantities of distance between them. So, considering possible distances between two mentioned cut-off walls lead to acceptable design and desirable implementation of this seepage control equipment. In the present study, 120 seepage simulation scenarios through dam foundation are solved based on different depths of the cut-off walls and variations of the distance between them. Following, MLP neural network meta-models are utilized to simulate the interaction between hydraulic behavior of cut-off walls and seepage flow through dam foundation. Then, NSGA-II, as an efficient multi-objective optimization algorithm, specifies the optimal amounts of design decision variables, namely, optimum depth of cut-off walls and optimum distance between them, while the five objectives of optimization which are seepage flow discharge through foundation, uplift force, horizontal and vertical exit gradients at toe of dam and overall cost of applying cut-off walls would be minimized.

3 Results and Discussion

The developed MLP neural network meta-models are trained and validated on the basis of the results of the seepage model of Yusufkand Mahabad diversion dam which are analyzed by FEM. For this aim, 70% and 30% of the input-output data have been utilized for training and validating the proposed model, respectively. The trained MLP models are used to simulate the hydraulic behavior of cut-off walls. The five objectives of optimization are seepage flow discharge through foundation, uplift force, horizontal and vertical exit gradient at toe of dam and overall cost of applying cut-off walls which all need to be minimized. With respect to these goals, the MLP neural network simulation models estimate the hydraulic features of cut-off walls considering their depth and the distance between them as decision variables.

In order to train and validate the MLP neural network meta-models the results of seepage model in Seep/W module of Geostudio software for different possible cases of decision variables were used. The results of MLP meta-models for estimating the seepage flow and uplift force discharge through foundation of Yusufkand Mahabad diversion dam are illustrated in Fig. 2a and b, respectively. Also, the results of MLP meta-models for estimation of vertical and horizontal exit gradients at toe of the intended dam are shown in Fig. 2c and d, respectively. As shown in Fig. 2, values of R^2 for the trained and validated data illustrate the acceptable accuracy of the developed MLP meta-models to estimate the hydraulic characteristics of cut-off walls in seepage control.

To estimate the overall cost of appliance of cut-off walls a multi-variable linear regression is used based on depth of the upstream and downstream cut-off walls, as two of the design decision variables. The acquired equation (see eq. 5) is then applied as the cost objective in GA optimization model.

The proposed multi-objective optimization model based on NSGA-II is utilized to determine the optimum values for decision variables as a trade-off curve. As mentioned earlier in Section 2.1, the objectives of this optimization process are to minimize (1) seepage flow discharge; (2) uplift force; (3) horizontal exit gradient; (4) vertical exit gradient at toe of dam and (5) overall cost of applying cut-off walls.

According to Figs. 3a(1), 3a(2) and 3a(3), it appears to be trivial that a direct relationship exists between each set of 2 objectives. For example, in Fig. 3a(1), as the objective 1 (seepage flow discharge) increases, the amount of objective 3 (horizontal exit gradient) grows. On the other hand, an indirect relationship is observed between each set of 2 objectives in Figs. 3b(1), 3b(2) and 3b(3), separately. As it is depicted in Fig. 3b(1), the increasing process in objective 4 (vertical exit gradient), causes the amount of objective 5 (overall cost of applying cut-off walls) to reduce. Referring to Figs. S3a, S3b and S3c (Online Resource), it seems that objective 2 (uplift force under dam body) is independent of the variations of objectives 3 (horizontal exit gradient at toe of dam), 4 (vertical exit gradient) and 5 (overall cost of applying cut-off walls) in each separate figure. By way of illustration,

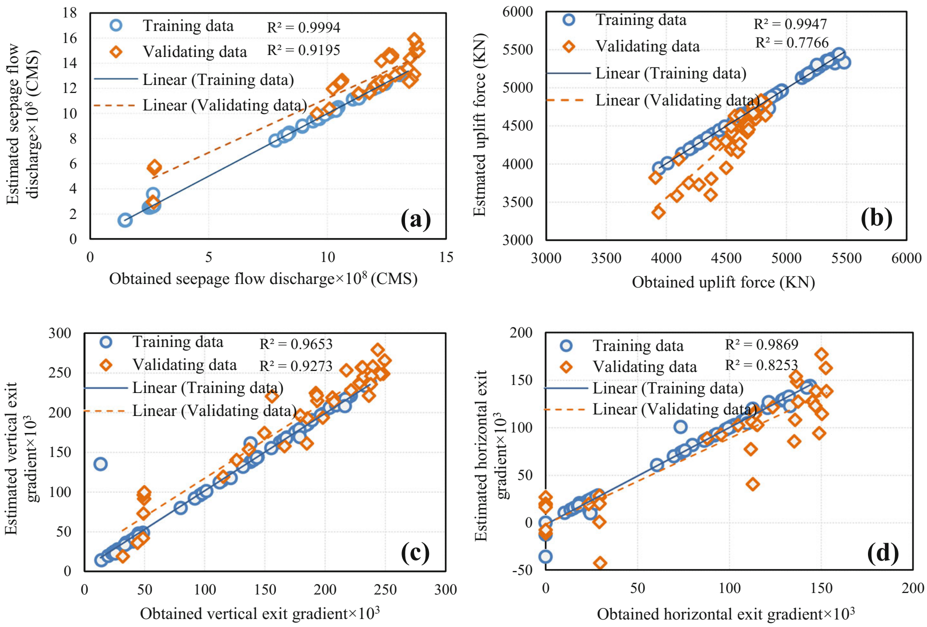


Fig. 2 Results of developed MLP meta-models to estimate a) seepage flow discharge, b) uplift force, c) vertical exit gradient, d) horizontal exit gradient at toe of Yusufkand Mahabad diversion dam in train and validation stages

the Fig. S3b (Online Resource) indicates that as the objective 4 (vertical exit gradient) escalates, the amount of objective 2 (uplift force under dam body) remains in a constant range.

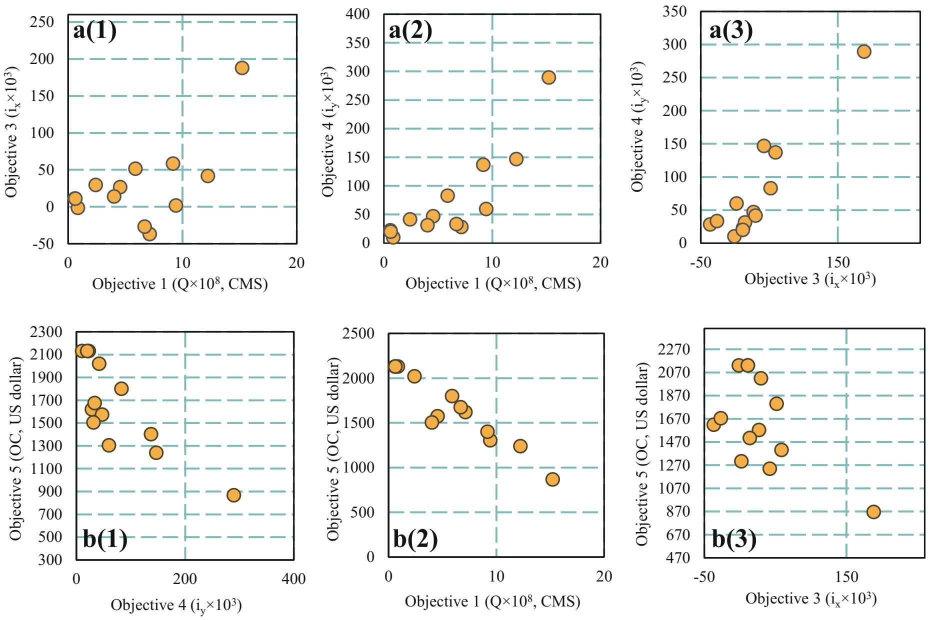


Fig. 3 Correlation between objectives of the NSGA-II optimization model a) objectives with direct correlation, b) objectives with indirect correlation, (Objectives 1 to 5 are seepage flow discharge, uplift force, horizontal and vertical exit gradient at toe of dam and overall cost of applying cut-off walls, respectively.)

Table 1 represents the Pareto-optimal solutions with their objectives' values h_1, h_2, …, h_5 and demonstrates their corresponding design decision variables x_1, x_2 and x_3.

As it is shown in Tables 1, 13 Pareto-optimal solutions exist which required to be assessed to characterize the compromise optimal solution, Thus, PROMETHEE decision making model and Nash-Harsanyi bargaining model are utilized. Table 2 consists of the final outcomes of applying two mentioned models to find the compromise alternative, namely, PROMETHEE model designates the 3rd solution as the compromise optimal solution among 13 Pareto-optimal solutions obtained from trade-off curves and also Nash-Harsanyi bargaining model selects the 10th alternative. The 3rd solution is related to the design decision variables $x_1, = 10\ m$, $x_2 = 3.84\ m$, $x_3 = 32\ m$ and also the 10th solution gives the values of $x_1 = 2.47\ m$, $x_2 = 10\ m$, $x_3 = 29.22\ m$ for design of the upstream cut-off wall, the downstream one and distance between them, respectively, when hydraulic features and overall cost are considered simultaneously. To illustrate, the 3rd cut-off wall design alternative leads into the seepage flow discharge of 7.13 *CMS*, while the quantity of this objective through the 10th cut-off wall design alternative equals with 4.02 *CMS*. According to the explanation in sections 2.2 and 2.3, both of these Pareto-optimal ranking methods that have been used to find the most suitable design alternative, are related to different base theorems. Nash-Harsanyi model is a solution concept in non-cooperative game theory in which players' preferences and disagreement points are considered within, while the PROMETHEE decision making model is mostly appropriate as a solution to the problems defined with a choice among alternatives and it is based on the manner of outranking. With respect to these and according to Table 2, the order of solution numbers presented by PROMETHEE model differs from that in Nash-Harsanyi bargaining model. For instance, 8th solution is ranked as 12th compromise alternative in the PROMETHEE model, but the same solution is ranked as 5th compromise alternative in accordance with Nash-Harsanyi bargaining model application.

In order to designate weights of the objectives of optimization w_i where $i = 1, 2, …, 5$ and $\sum_{i=1}^{m} w_i = 1, w_i \geq 0$, to use in the optimal solution choosing procedure, sensitivity analysis is

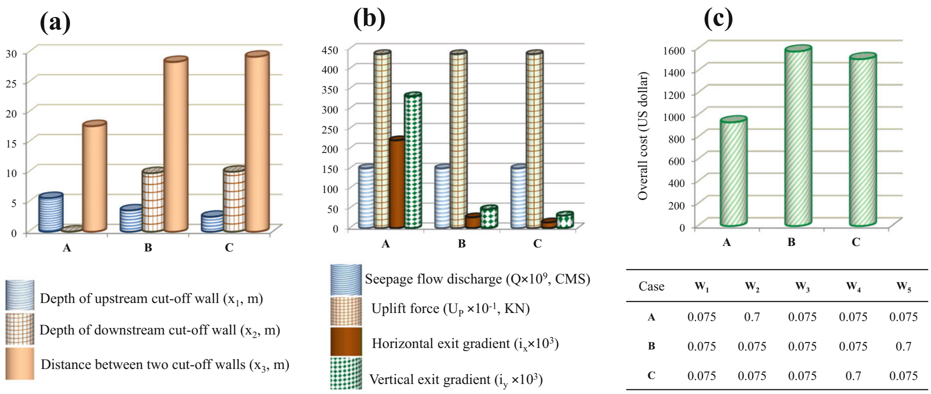
Table 1 Pareto-optimal solutions and their corresponding decision variables as well as values of objective functions

No.	Design decision variables					Objectives		
	Depth of upstream cut-off wall (x_1, m)	Depth of downstream cut-off wall (x_2, m)	Distance between two cut-off walls (x_3, m)	$h_1 = Q \times 10^8$ (*CMS*)	$h_2 = U_P$ (*KN*)	$h_3 = i_x \times 10^3$	$h_4 = i_y \times 10^3$	$h_5 = OC$ (\$)
1	10.00	10.00	28.5	0.6	4752.3	11.1	20.0	2131.9
2	10.00	10.00	32.0	0.9	4651.4	−1.4	10.3	2131.9
3	10.00	3.84	32.0	7.13	3871.2	−36.7	28.3	1620.0
4	10.00	10.00	27.3	0.6	4771.4	11.3	22.6	2131.9
5	10.00	0.06	28.5	9.4	3675.1	2.0	59.9	1305.1
6	2.72	2.08	18.0	15.2	4605.5	188.2	289.5	868.0
7	8.82	7.20	27.1	5.9	4506.7	51.6	82.9	1801.4
8	3.24	7.99	29.0	9.2	4960.1	58.7	137.0	1402.6
9	3.54	9.76	28.4	4.5	5389.7	26.9	47.1	1575.0
10	2.47	10.00	29.2	4.02	5482.4	14.1	31.2	1506.0
11	9.96	4.56	31.2	6.7	3955.5	−26.7	33.3	1676.5
12	2.98	6.29	29.6	12.2	4775.9	41.9	146.8	1239.7
13	9.60	9.06	25.5	2.4	4618.0	29.6	41.7	2021.0

Table 2 Rank of the Pareto-optimal solutions using PROMETHEE and Nash-Harsanyi models

Rank	PROMETHEE		Nash-Harsanyi	
	Solution number	Net $\varphi(a)$	Solution number	Nash product
1	3	0.018	10	660.16
2	5	0.017	9	606.31
3	11	0.016	12	316.56
4	2	0.010	6	285.64
5	1	0.008	8	−195.21
6	4	0.007	5	−463.79
7	13	0.006	7	−567.98
8	10	0.003	13	−708.43
9	7	0.003	4	−718.47
10	9	0.001	1	−731.98
11	12	−0.003	3	−751.68
12	8	−0.004	11	−758.24
13	6	−0.017	2	−803.86

accomplished considering the results of Nash-Harsanyi bargaining model. Hence, effect of changing the weights was checked on amount of the best optimal solution that would be chosen through Nash-Harsanyi bargaining model. At the first step, the difference between the amounts of weights was slightly changed and no variation was seen in the amount of the best optimal solution chosen by Nash-Harsanyi bargaining model. Situations in which slight changes of the weights of objectives had no effect on amount of the best optimal solution, are mentioned in Table S3 (Online Resource, Tables S3). Then, amounts of the weights assigned to the objectives of optimization were changed to reach the threshold in which the best optimal solution on the Pareto front, chosen by Nash-Harsanyi bargaining model, started to change. Accordingly, details of changing the weights after the mentioned threshold show that by increasing weight of uplift force to get more than other weights (set A of weights in Fig. 4), the compromise optimal solution would be the 10th one (see Table 1). Following, in set B of the weights, weight of overall cost is increased to become more than other weights, so the compromise optimal solution is chosen as the 9th one.



Case	W_1	W_2	W_3	W_4	W_5
A	0.075	0.7	0.075	0.075	0.075
B	0.075	0.075	0.075	0.075	0.7
C	0.075	0.075	0.075	0.7	0.075

Fig. 4 Sensitivity analysis of a) design decision variables, b and c) objectives of optimization to determine the effective set of weights*. * Weights assigned to the five objectives of optimization which are seepage flow discharge, uplift force, horizontal and vertical exit gradient at toe of dam and overall cost of applying cut-off walls, respectively

To complement the topic, Fig. 4a depicts the amounts of design decision variables versus sets A, B and C of weights. As shown in Fig. 4a, depth of the downstream cut-off wall is nearly zero in set A of the weights, which is not an accepted value due to the direct effect of downstream cut-off wall on exit gradient reduction (Tuzkaya et al. 2008). For sets B and C of weights, the distance between two cut-off walls have equal amounts as well as the depth of downstream cut-off in both sets. Thus, according to the lower depth of upstream wall in set C of weights which leads into less overall cost comparing with set B (Fig. 4c), set C is chosen as the effective set of weights. Fig. 4b shows the amounts of objectives versus sets A, B and C of weights, in which seepage flow discharge and uplift force have nearly the same amounts in sets A, B and C of weights, separately, while the values of exit gradient (horizontal and vertical) reduces remarkably due to the change from set A of weights to set C. Thus, the set C of weights is designated as the effective set of weights and represents the 10th optimal solution. According to Fig. 4c, although the minimum amount of cost objective is not assigned to set C of weights, this set is being chosen as the acceptable set of weights due to the importance of safe values of exit gradient effective to dam stability. Based on Fig. 4, when the maximum weight (0.7) was assigned to the 4th objective of the optimization (set C of the weights), the acquired optimal solution was exactly the same as results of the situation in which the maximum weight (0.7) was assigned to the 1st objective (seepage flow discharge) and the 3rd one (horizontal exit gradient), separately. Hence, repeated results were not mentioned in Fig. 4.

4 Conclusion

One of the main reasons of the seepage flow through a diversion dam foundation is the difference between the water levels in the upstream and the downstream. Thus, the seepage flow and its consequences should be investigated to be controllable. In this research, a simulation-optimization model has been developed to determine the compromise optimal design characteristics of cut-off walls under Yusufkand Mahabad diversion dam, located in Iran. For this aim, the MLP neural network models were used to estimate the hydraulic behavior of cut-off walls based on the results of the numerical solution of the seepage problem beneath the dam that had been analyzed by simulating through Seep/W module in Geostudio software considering variations of design decision variables. The trained MLP neural network models were then linked to a robust multi-objective optimization algorithm in order to find the optimum distance between the two cut-off walls and their optimum depth. The optimal amounts of design decision variables ensure the decision makers to have safe foundation of diversion dam with long-term service life as predicted. Regarding the overall cost of applying cut-off walls as one of the objectives of the optimization model makes the study more comprehensive as a result of the fact that economic considerations are among the important priorities of stakeholders like construction employers who tend to have cost-effective projects. On the one hand, conflicting interests of different stakeholders are considered through the simulation-optimization methodology using Nash-Harsanyi bargaining model and PROMETHEE decision making model to select the compromise non-dominated solution among the available Pareto-optimal choices. This point can help the decision makers to choose appropriate weights for objectives of the optimization model based on their preferred standpoints. The obtained results illustrate that the proposed methodology is efficient in determining the optimal design features of cut-off walls under a diversion dam. For future studies based on the present study, existing uncertainties of dam design like geotechnical parameters of the soil can be considered in design of seepage control devices of diversion dams such as cut-off walls and aprons.

Compliance with Ethical Standards

Conflict of Interest The authors declare that they have no conflict of interest.

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