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Optimization of Invasive Weed for Optimal Dimensions of Concrete Gravity Dams

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ABSTRACT

Dam construction projects are considered among the most extensive and expensive projects. It is always appropriate and optimal for such concrete structures to reduce the volume of concrete and consequently reduce construction costs. In this study, invasive weed optimization software GNU octave was used to find the dimensions of the concrete gravity dam Koyna located in India optimized stability constraints. For this purpose, a cross-section with a length unit consisting of eight geometric parameters was used as input variables, and other geometric parameters were defined using these variables. The result showed that invasive weeds are well-optimized dimensions of the dam as the volume of concrete in the construction of the dam at the current level measures 3633 cubic meters that optimal dropped 3353 cubic meters, which is a mean of 7.7% of the value of the objective function (the volume of concrete in dams) is reduced. This amount of concrete decreased the construction of the dam, saving the cost and is more economical.

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1. Introduction

The operation of dam reservoirs is one of the water resources managers goals, and various methods have been proposed to solve such problems. With increasing dimensions, the number of variables, and constraints, the possibility of solving such problems with conventional optimization and explicit computational methods is reduced. It is challenging to achieve an optimal solution in these conditions. Thus, the use of meta-exploration methods or evolutionary algorithms, which of course, do not guarantee the achievement of an absolute optimal solution, but can create different answers [1–6] have received much attention [7] using the quasi-programming algorithm. Simoes 1994 [8] obtained the optimal shape of a weighted concrete dam under the influence of static and dynamic forces. Cai et al. combined the GA algorithm with linear programming and successfully solved significant nonlinear water resources management problems [9]. Chen used this algorithm to obtain the command curves of a single-reservoir system and evaluated it as very effective for optimizing completely nonlinear systems [10]. Mollazadeh et al. determined the cross-section of a weighted concrete dam by a genetic algorithm [11]. Bozorg Haddad et al. [12] used the bee mating optimization algorithm (BMO) in the problems of optimal operation of dam reservoirs. They obtained encouraging results compared to other meta-exploration algorithms in solving problems.

In a study, Kumar et al., 2006 [13] used a genetic algorithm to optimize the performance of the Matlab Raha single-purpose dam reservoir for irrigating crop plants. The results showed that the optimal performance is obtained using linear programming. Afshar et al., 2007 [14] presented an extended bee mating algorithm and used it to optimize a continuous single-reservoir system with nonlinear limit functions.

Comparing the results with the results obtained from Lingo software has shown that this algorithm's convergence to the absolute optimal solution is very fast. Dariane and Moradi [15] used the continuous ant algorithm in optimizing the operation of the Karkheh basin reservoirs and compared the results with the genetic algorithm. This short-term model showed the superiority of the continuous algorithm over genetics in their studies compared the dimensions of a weighted concrete dam using a genetic algorithm and a particle swarm optimization algorithm and compared the two algorithms in terms of accuracy and speed of response. Azarfza et al. [16] optimized the reservoir for the 5-year flow of the Chai River to meet downstream needs, including drinking, agriculture, and the environment. This study compares annealing algorithms, genetics, and particle swarm, and the particle swarm optimization algorithm is more effective than other methods. Dariane and Farahmandfar [17] used a bee optimization algorithm to optimize the operation of the Karkheh multi-reservoir system in southwestern Iran. After comparing it with particle swarm algorithms and genetics, they concluded that Bee optimization has been more efficient. Ghodousi and Oskouhi [18] optimized the Koyna concrete weight barrier dimensions using the nonlinear LINGO11 model. Their research showed that optimizing the dimensions of the dam compared to the actual model has decreased by 2.26 percent. Based on previous research, the invasive weed optimization algorithm has not been applied to optimizing the dimensions of a weighted concrete dam, so this study aims to utilize the invasive weed algorithm (IWO) optimization method for the optimal construction of Koyna weight concrete dams located in India in order to reduce the amount of concrete used to build the structure and reduce costs associated with its construction. Alikhani., 2019 [19], in a study, used the ABC artificial bee colony method to optimize the double-arched dam. Also, the number of divisions n = 5 leads to a decrease of 23.14% compared to the actual volume of the dam.

In the design of gravity dams, several geometric parameters are taken into account depending on the design criteria, the site specifications, and the height requirements. An executive option is one that is both sustainable and cost-effective. Considering geometric parameters as decision variables, barrier weight was regarded as the objective function. The geometric parameters of the dam are determined by the model in order to minimize the number of materials used in the construction. For the evaluation of the proposed method, the Koyna dam dataset was used, and the results were compared with those obtained from genetic algorithms (GA), honey bee mating (HBMO), and colonial competition (ICA).

Based on the results of the EA method, the volume of concrete used and the area of the Koyna dam have been reduced by 9.87 and 10.40 percent, respectively. Compared to genetic optimization (GA), honey bee mating (HBMO), and colonial competition (ICA), the EA algorithm demonstrated better efficiency in achieving the optimal dam section dimensions. In addition, the EA algorithm improves by 8%, 6%, and 11% compared to ICA, HBMO, and GA algorithms, respectively [20].

As concrete is increasingly used in construction and infrastructure, global pollution has increased. Thus, the construction industry must always use its raw materials sustainably without compromising the functionality of the structure. For facilities that are being constructed, the goal of design optimization is to provide an engineered solution that is both reliable, environmentally sustainable, and cost-effective. In conjunction with appropriate algorithms, ANSYS has been used to model and analyze the non-overflow section of the concrete gravity dam. In order to minimize the volume of concrete, while meeting the loading and factor of safety requirements specified in the IS codes, the geometrical properties of the dam are taken into account as design variables (for a fixed height and freeboard).

As part of our current research, we are attempting to reduce the volume of the non-overflow section of a concrete gravity dam in order to reduce its weight, which is always directly proportional to its volume. As a matter of economics and sustainability, it is imperative to reduce the dam's weight [21].

It is important to take into account uncertainties such as material randomness, manufacturing anomalies, and external loads when designing engineering structures. As a result, reliability-based design optimization (RBDO) is frequently used to ensure economic aspects without compromising safety [22].

As a result of the research conducted by scientists over the past few years, many empirical models have been presented attempting to estimate the longshore sediment transport rate, but these methods have been calibrated and applied to specific bed profile and sediment size conditions. An empirical relationship between sediment transport and observation and measurement data is commonly calculated through linear or exponential regression, but a soft computation approach may produce more accurate predictions. Comparisons will be made between the results and the top three most popular empirical equations. Four stations were sampled daily between March 2012 and June 2012. ANFIS's adaptive structure allows it to better fit complex systems than existing regression-based empirical equations for estimating alongshore sediment transport rates [23].

It is useful to have an accurate correlation for smooth sphere drag coefficients in particle technology. The purpose of this study is to develop highly accurate drag coefficient correlations for Reynolds numbers from low to very high (up to 106) by using a multi-gene Genetic Programming (GP) procedure. In GP, the structure and parameters of the model are simultaneously determined. Traditionally, regression analysis involves imposing a model structure and assigning parameter values. Thus, it is possible to optimize not only the parameters, but also the structure of a model with the GP approach. We have developed two new, highly accurate models during this study, one for the region before drag dip, the other for the entire Reynolds number range up to 106, including the transient region between laminar and turbulent flows [24].

In cross-sectional mixing, the longitudinal dispersion coefficient plays a crucial role in determining the distribution and transmission of pollution. There is, however, great uncertainty associated with existing prediction techniques. Modeling was conducted using the Bayesian network (BN) approach. The best model structure was determined by examining dimensional and dimensionless input variables. Using the clustering method, the data were categorized into groups of similar characteristics to increase the model's performance [25].

In this study, we aim to improve the accuracy of tunnel boring machine (TBM) performance predictions, which is one of the most challenging and important aspects of tunnel construction. A novel methodology based on dimensional analysis (DA) and multi-gene genetic programming (MGGP) is proposed in order to obtain an accurate and practical model for predicting TBM performance. In order to predict TBM performance more efficiently, DA enables the introduction of three dimensionless parameters. Various features associated with TBMs and rocks can be represented by these parameters [26].

The use of spillways with labyrinths remains a popular control method. Based on the angle between the crest alignment and flow direction, the relative depth of flow over the spillway, and the height of the crest, an Adaptive Neural Fuzzy Inference System (ANFIS) model was developed for the labyrinth spillway. By considering certain hydraulic conditions as constraints to the optimization process, differential evolution (DE) and genetic algorithms (GA) were used to minimize spillway costs [27].

The grasshopper algorithm was compared with the particle swarm optimizer (PSO), Gray Wolf optimizer (GWO), and LINGO11 algorithm. It can be concluded from the results that the grasshopper algorithm's optimization method is superior to other methods. A comparison of the optimized concrete volume with the PSO method found a volume reduction of 378 cubic meters, 10.4%, 431 cubic meters, 11.86%, 82 cubic meters, 2.25%, and 498 cubic meters, 13.7%. By considering seismic forces, the volume of concrete was reduced by 10.99%. Based on the grasshopper algorithm, the best model has a 13.7% reduction in concrete volume, equivalent to 498 cubic meters, when applied to a situation without seismic forces. As a result of the construction of the Koyna dam, 3633 cubic meters of concrete were used, of which 3551 cubic meters were optimized using the LINGO11 method within the GWO method 3255, within the PSO method 3202, and within the GOA method 3138, which, in general, resulted in 82, 378, 431, and 495 cubic meters of optimization [28].

2. Study limitations

In this research, the invasive weed algorithm has been used to achieve the best dimensions of the Koyna weight concrete dam and achieve near-optimal solutions so that the studied dam has the most suitable volume of concrete consumption.

A concrete gravity dam located in India, called Koyna, was optimized based on dimensions using GNU octave's invasive weed optimization program. Using eight geometric parameters as input variables, a cross-section with a length unit was used to define other geometric parameters.

3. Methods

An algorithm for finding an exact or approximate solution to an optimization problem or a search problem is called a genetic algorithm. Heuristics for global search are also known as global search heuristics. These techniques are derived from evolutionary biology, including inheritance mutation, selection, and cross-over. As a result of these algorithms, the program is able to automatically improve its parameters. Various applications of genetic algorithms are described in this paper, as well as the integration of genetic algorithms with object-oriented programming approaches [29].

Particle swarm optimization (PSO) is widely used as a swarm-based algorithm. In spite of its good optimization performance, the original PSO still suffers from premature convergence. PSO has been modified by many researchers. Consequently, many variants perform better by a small or significant margin. PSO has been modified in four ways: by modifying its control parameters, by combining it with other meta-heuristic algorithms such as genetic algorithms and differential evolution, by cooperating, and by using multi-swarm algorithms. The present paper provides an overview of PSO, covering basic concepts, binary PSOs, neighborhood topologies in PSOs, recent and historical variants, engineering applications of PSOs, and their limitations. We suggest eight specific research directions for further improving PSO performance as a final point [30].

Since Direct Torque Control (DTC) offers several advantages over other control methods, it is an optimal method for controlling the behavior of alternative motors; however, speed overshoots, fluxes, and torque ripples remain the major limitations to its robustness. In linear systems, the Proportional Integrator Derivative (PID) controller is known for its higher robustness. However, when the parameters of a nonlinear system change, the PID controller is not as responsive. PID controllers are often designed to adapt their behavior to the system's nonlinearity when perturbations occur internally or externally, using optimization algorithms to generate the controller's gains whenever an external or internal perturbation occurs. To achieve this objective, this research will analyze and validate the dSPACE Board DS1104 theoretically and experimentally by using a new proposed PID speed regulation method, based on Ant Colony Optimization (ACO) for DTC, which has been applied to both sides of a Doubly Fed Induction Motor (DFIM) to overcome previous limitations. Using a cost function such as Integral Square Error (ISE), a new combined ACO-DTC strategy was developed to optimize PID controller gains. To validate the objectives of the proposed strategy, an implementation of Matlab/Simulink is performed. Using simulations and experiments obtained from Matlab and Control Desk, we have demonstrated the effectiveness of the proposed ACO-DTC in dealing with nonlinearities in the system. The enhancement of global system performance can be attributed to a number of factors [31].

By integrating the invasive weed optimization with biomass and product dynamics analysis, a waste the product approach was proposed for tuning surroundings-threat soybean husk toward lipolytic enzyme. Based on the nonlinear regression model, the invasive weed optimization produces a 47 % increase in lipolytic enzyme using the optimization parameters of 7% Sigma Final, 9% exponent, 5 Smax, 35 population size, and 99 generations. As a result of the biomass study, 0.0239 max, 8.17 XLimst, and 0.852 RFin values have been determined. As a result of the dynamic product studies, it has been determined that kst, kdiv, and PFin have kinetic parameters of −0.0338, 0.0896, and 68.1, respectively. By introducing the novel approach of "Invasive Weed Optimization" coupled with "Biomass and product dynamics" to the field of bioprocessing, the present study advanced the zero-waste (soybean husk) to product (lipolytic enzyme) approach [32].

Koyna concrete dam weighs 103.23 meters and is built on the river Koyna in India. The height of flood level and typical of this dam is 103 meters and 91.75 meters, respectively. The width of the dam crown is 14.8 meters, and the volume of the reservoir is 2797.4 million cubic meters. The exploitation of the dam began in 1964. Table (1) shows the Koyna weighted concrete dam, 2005 [33]. In Table (1): Hu, the upstream water level of the dam in normal condition, Hd, the downstream level of the dam down in the normal state, Huf, the upstream water level in the flood state and Hdf, downstream water level in the flooded state, and variables b1 to b8 dimensions of the dam Concrete is the weight of Koyna. Figure (1) also shows a two-dimensional view of the Koyna weighted concrete dam cross-section.

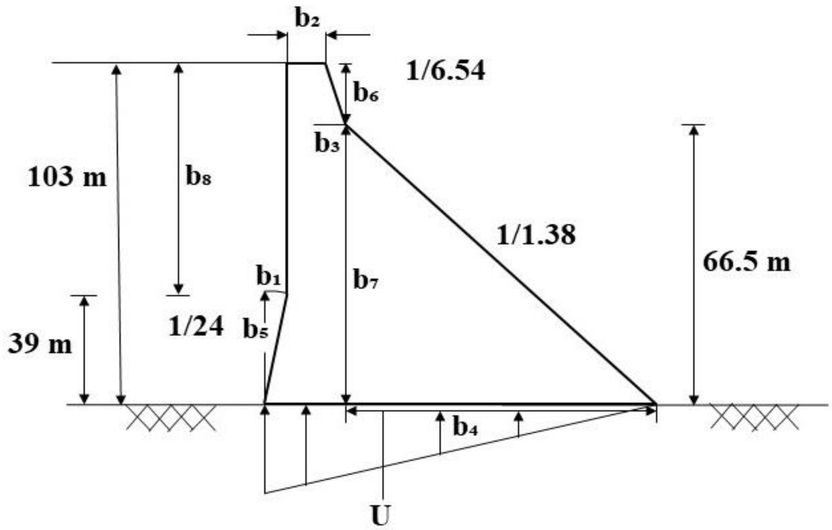

Fig. 1. Two-dimensional view of the cross-section of Koyna weighted concrete dam.

In general, optimization problems can be divided into constrained and non-constrained problems. In optimizing structures such as dams, various variables mainly used to limit stresses and deformations are often defined as constrained. One of the new optimization methods is the grass optimization algorithm.

Weeds are plants that are highly stable and adaptable to the changing environment and whose invasive growth poses a significant threat to crops. The use of their properties can, therefore, result in a robust optimization algorithm. This algorithm attempts to mimic the power of adaptability and a random population of weeds in a simple but effective way. This method was first proposed in 2006 by Mehrabian and Lucas in an article. They tested the efficiency and effectiveness of the weed algorithm using multidimensional pattern functions, known as local and absolute extremes. They compared them with standard algorithms, such as genetics and incremental refrigeration. Their results showed that the performance of weeds in solving continuous and significant problems is better than other algorithms. When determining the optimal dimensions of a weighted concrete dam, the size of the dam is an important decision variable, as is the coefficient of confidence against overturning and slipping. As the child's seeds seek better resources in the environment, a random variable with a normal distribution describes their position relative to the parent plant.

Table 1
Geometric-hydraulic dimensions of Koyna concrete weight dam.

Variable	H_{df} (m)	H_{uf} (m)	H_d (m)	H_u (m)	b_8 (m)	b_7 (m)	b_6 (m)	b_5 (m)	b_4 (m)	b_3 (m)	b_2 (m)	b_1 (m)	V (m^3)
the amount of	0	103	0	75/91	64	5/66	5/36	39	19/48	6/5	8/14	63/1	3633

These seeds play the most crucial role in finding the best environment for living, both in nature and in the algorithm. After growing and becoming a plant, each seed reproduces new seeds and spreads them in the environment. In the continuation of this process, the weaker plants are eliminated from a specific limit with the increase of the plant population. The best plant is selected from the population at the end of each repetition. This algorithm calculates the number of offspring for each plant from Equation (1).

$$\boldsymbol{S} = \left[\boldsymbol{S_{min}} + (\boldsymbol{S_{max}} - \boldsymbol{S_m})\frac{f - f_{Worst}}{f_{Worst} - f_{Best}}\right] \tag{1}$$

Where S is the number of seeds per plant, $\boldsymbol{S_{min}}$ and $\boldsymbol{S_{max}}$ are the maximum number of seeds a plant can have, respectively, $\boldsymbol{f}$ is the fit of each plant, $\boldsymbol{f_{Worst}}$, and $\boldsymbol{f_{Best}}$ are the worst and best fit of the plant, respectively. The offspring of seeds with a normal distribution in Equation (2) are scattered around the parent plant.

$$\Delta \boldsymbol{x_i} = N\ (0,\sigma^2) \tag{2}$$

In Equation 2, distance Δx_i is the distance of the seed from the parent plant in line i, zero is the mean of the normal distribution, and σ^2 is the variance of this distribution obtained from Equation (3).

$$\boldsymbol{\sigma_t} = \left(\frac{T-t}{T}\right)^{n} \left(\boldsymbol{\sigma_{initial}} - \boldsymbol{\sigma_{final}}\right) + \boldsymbol{\sigma_{final}} \tag{3}$$

Where $\boldsymbol{\sigma_t}$ is the value of variance in $\boldsymbol{t}$ the iteration, $\boldsymbol{T}$ is the maximum number of iterations, $\boldsymbol{t}$ is the number of each iteration, and n is a fixed number that controls the rate of decrease $\boldsymbol{\sigma}$. $\boldsymbol{\sigma_{initial}}$ and $\boldsymbol{\sigma_{final}}$ are the initial and final values $\boldsymbol{\sigma}$, respectively. In the initial repetitions, due to the higher value of $\boldsymbol{\sigma}$, the dispersion of the child's grains is higher. Then, by decreasing the value of $\boldsymbol{\sigma}$ in each repetition, the dispersion of the child's grains decreases. At the end of each repetition, as the population of plants increases from a specific limit, weaker plants (inadequate responses) are eliminated, and the most suitable plant (best response) is selected from the population. Figure (2) shows the rotation diagram of the algorithm developed in this research.

4. Problem modeling

The cross-sectional area of the dam is a function of the objective of the problem, so the aim is to reduce the amount of this surface, followed by a reduction in the volume of concrete. A general cross-section across the unit's width, including eight geometric parameters (b1 to b2), was considered design variables to optimize the dimensions of the studied concrete weight bar. Other geometric parameters were considered and defined dependently on these variables. All necessary forces and torques were determined according to design variables, normal stresses upstream of the dam, and reversal and slip reliability coefficients. The program was developed in the GNU Active software environment and was called a subroutine in the developed optimization model.

5. The forces acting on the cross-section of the weighted concrete dam

The forces acting on the dam can be generally divided into forces in the direction of stability and forces in the opposite direction of stability. The forces acting on the stability of the dam are: the force due to the weight of the dam, the vertical component of the hydrostatic force of water pressure (downward), and the force due to the pressure of sediments (downward), which is vertical It enters the body of the dam. The forces acting in the opposite direction of the dam stability are the horizontal component of the hydrostatic force of the reservoir water pressure, the compressive force, the seismic force (in the body and the reservoir of the dam), and the force due to the sediment pressure acting horizontally on the body of the dam enters. Loading of dams should be based on the most critical state. For this reason, this study to analyze the stability of the dam loading compounds in the case of extraordinary loading has been considered [34,35].

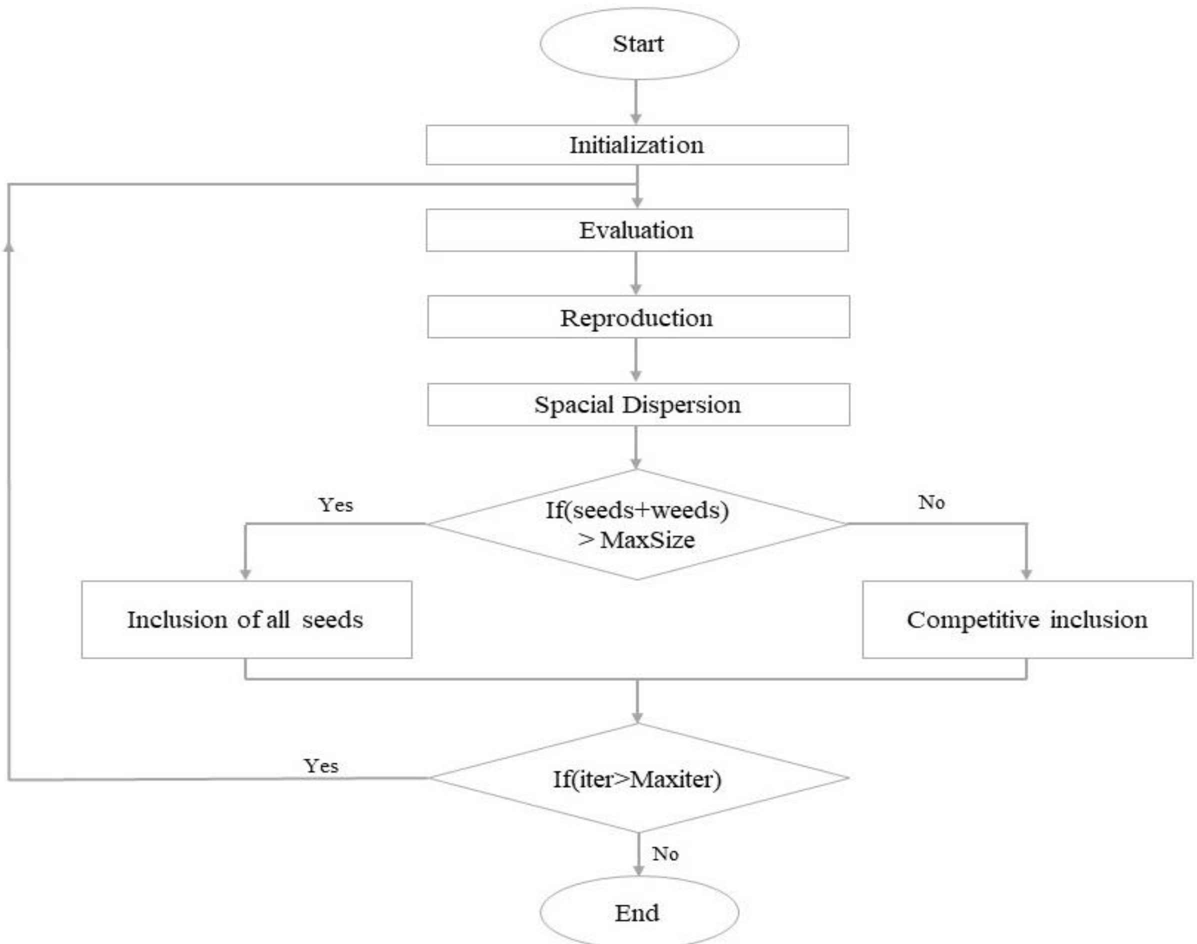

Fig. 2. Flowchart of the Invasive Weed Optimization Algorithm (IWO).

6. Optimization model of weighted concrete dam dimensions

In this research, the invasive weed algorithm has been used to achieve the best dimensions of the Koyna weight concrete dam and achieve near-optimal solutions so that the studied dam has the most suitable volume of concrete consumption. A dam construction problem aims to minimize concrete volume, and variables of interest include the weight dimensions of Koyna concrete.

The objective function in this problem is calculated as (4):

$$C = Min\ V(x) \tag{4}$$

$$V(x) = \begin{bmatrix} \left(\frac{1}{2} \times b_1 \times b_2\right) + +\left(b_2 \times (b_5 + b_8)\right) \\ + \left(\frac{1}{2} \times b_3 \times b_6\right) + (b_3 \times b_7) \\ + \left(\frac{1}{2} \times b_4 \times b_7\right) \end{bmatrix} \quad (5)$$

$V(x)$ is the volume of concrete used, and the parameters b_1 to b_8 are the decision variables or the exact dimensions of the Koyna weight concrete dam. Another critical factor in developing an optimization model is the application of constraints. Obstacles in this issue include the coefficient of reliability against slippage, overturning, and stress on the surface of the dam body, the allowable value of which must be controlled.

7. Slip reliability

Factors that can withstand the slip of the dam are the friction and shear strength between the two pieces or between the dam and the foundation at the base, which constitute the slip-resistant forces; Each dam must be designed so that these forces are more significant than the sliding forces. Accordingly, the slip reliability coefficient will be the ratio of the total vertical slip-resistant forces to the horizontal slip forces examined in the case. The first case assumes the disregard of the cross-sectional shear strength, in which case the slip reliability is obtained from Equation (6):

$$SF_s = \mu \frac{\sum F_v}{\sum F_H} \quad (6)$$

Where $\sum F_v$ is the sum of the vertical forces acting on the cross-section; $\sum F_H$ is the sum of the horizontal forces acting on the cross-section; μ is the coefficient of friction between the upper and lower sections. The value μ for concrete, building materials, and stone varies between 0.65 to 0.8, which is generally chosen to be 0.75. The slip reliability coefficient must be greater than one; in this case, if the shear strength is considered, the value of this coefficient will be greater than one, 2001 [36]. The second case is if the calculated reliability coefficient is less than one. In this case, it is necessary to add the shear friction coefficient of equation 7 by adding the cross-sectional shear strength:

$$SF_F = \frac{f \sum F_v + b_\sigma}{\sum F_H} \quad (7)$$

Where $\sum F_v$ is the vertical force acting on the dam; $\sum F_H$ horizontal force on the dam; Distance b base length at the studied surface; and σ is the allowable shear stress of the material at the shear surface. The allowable shear stress of concrete is about one-fourth of its shear strength or one-twentieth of its compressive strength. The allowable shear stress of concrete is considered between 7 and 14 kg / cm2. The static friction coefficient f for moving concrete on rock or concrete on the concrete surface often varies between 0.65 to 0.75, which is considered 0.7 on average. According to the US Civil Aviation Authority standard recommendation for short dams, in case of loss of life and property due to the dam's failure, 4 SFF ≥ should be considered., 1987

[37]. Another limitation considered in this case is the allowable amount of stress. The stresses created in the dam structure should be in a specific range of stresses. They should be designed so that the stress at any point of the dam and the foundation does not exceed the allowable stress limit and, if possible, all the resistance Used structures and foundations.

8. Vertical tension in the body of the dam

To study the vertical stress on the surface of the dam body in the mirage and downstream, two equations (8) and (9) are used:

$$\boldsymbol{\sigma_u} = \frac{\sum \mathbf{F_v}}{\mathbf{b}} - \frac{6\sum \mathbf{M_o}}{\mathbf{b^2}} \tag{8}$$

$$\boldsymbol{\sigma_d} = \frac{\sum \mathbf{F_v}}{\mathbf{b}} + \frac{6\sum \mathbf{M_o}}{\mathbf{b^2}} \tag{9}$$

In which $\boldsymbol{\sigma_u}$ and $\boldsymbol{\sigma_d}$ are the vertical stresses at the body surface in the mirage and stream, respectively; $\sum \mathbf{M_o}$ is the total torque of the forces acting on the dam up to the studied surface relative to the center of the surface, and $\sum \mathbf{F_v}$ is the sum of the vertical forces. This study considered forces in the direction of positive gravity, in the opposite direction of negative gravity, and torques in the opposite hand. For the dam to be stable against the vertical stress created, $\boldsymbol{\sigma_u}$ and $\boldsymbol{\sigma_d}$ must be positive when the tank is full or empty, and this value must not exceed the allowable compressive strength. Tested concrete compressive strength for dams is usually 140 to 350 kg /cm2.

9. Stability against overturning

Suppose the anchors resistant to the claw of the dam are about 1.5 to 1.7 times more than the overturning anchors to the same point. In that case, the dam remains stable against the overturning, the relationship of which is presented in (10):

$$\boldsymbol{SF_o} = \frac{\sum \boldsymbol{M_R}}{\sum \boldsymbol{M_o}} = \mathbf{1.5 - 1.7} \tag{10}$$

$\boldsymbol{M_R}$ is the torque of the resisting forces, the Torque of the driving forces entering the dam.

10. Discussion

Using an invasive weed optimization model, the dimensions of the Koyna concrete weight barrier were optimized. There are different repetitions and sprayings in the program, and the total number of weeds in the program is 200. Presented in Table (2) are the results obtained after 10 times of program execution and after 150 times of sowing based on the values of the decision variables and the objective function. The results are shown in Figure (3). According to the Table, the optimal volume of the dam is 3353 cubic meters, i.e., 7.7% less than the existing dam.

Table 2
Existing and optimal dimensions of Koyna weighted concrete dam using invasive weed model (m) development.

	b_1	b_2	b_3	b_4	b_5	b_6	b_7	b_8	Objective function
Available value	63/1	8/14	6/5	19/48	39	5/36	5/66	64	3633
Optimal value	14/1	39/13	53/4	83/47	09/39	17/36	09/66	1/64	3353

In a study using the nonlinear LINGO11 model, they reduced the dimensions of the Koyna concrete weight barrier by 2.26%. Also, in another study, using the beekeeping mating algorithm, they reduced the volume of the Koyna weight concrete dam by 8.82%. Figure (4) also shows the objective function changes ten times of program execution and at the end of 150 times of sowing. As shown in Figure (4), the best value of the objective function is obtained ten times of program execution and different sprays in the 150th spraying, equal to 3353 cubic meters. How the objective function changes during spraying are performed 10 times, and different spraying is shown in Figure (4). The values of the objective function and the optimal decision variables of this problem, obtained in the 150th seed and the tenth iteration of the program, are compared with the dimensions in Table (3).

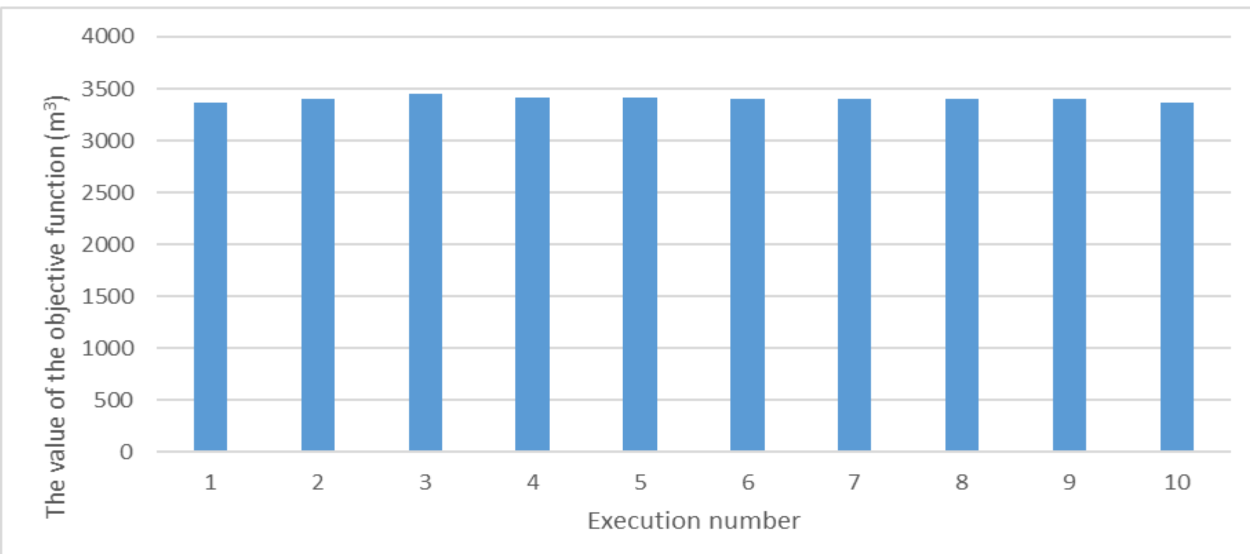

Fig. 3. Diagram of changes in the objective function at ten times of program execution and at the end of 150 times sowing.

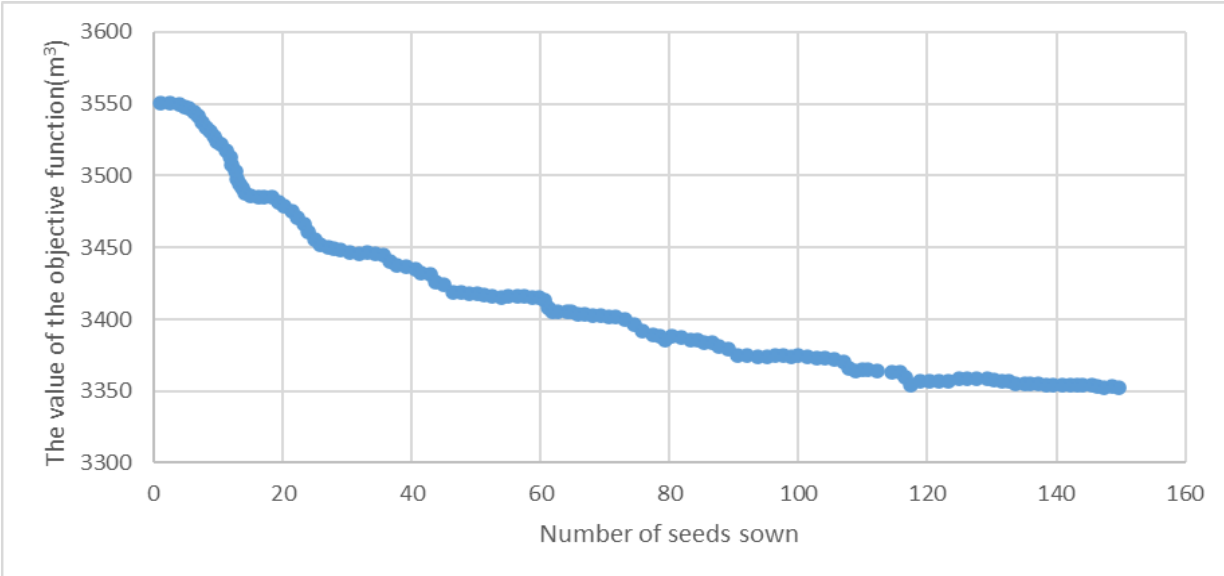

Fig. 4. How to change the value of the target function in the scatter plot Differently in the best ten times run.

Table. 3
Values of decision variables and objective function in 10 times of program execution and at the end of 150 times of sowing.

Repetition / Paramet	1	2	3	4	5	6	7	8	9	10
b1(m)	47/1	84/0	03/1	56/1	01/1	32/1	07/1	49/1	92/0	14/1
b2(m)	43/13	64/13	94/13	72/13	71/13	41/13	62/13	59/13	54/13	39/13
b3(m)	64/4	74/4	71/4	65/4	69/4	84/4	77/4	67/4	85/4	53/4
b4(m)	68/47	02/48	94/47	84/47	08/48	92/47	85/47	9/47	92/47	83/47
b5(m)	98/38	97/38	05/39	17/39	98/38	02/39	93/38	88/38	19/38	09/39
b6(m)	1/36	03/36	89/35	21/36	40/36	38/36	42/36	35/36	24/36	17/36
b7(m)	85/65	96/65	23/66	66	91/65	21/66	13/66	05/66	94/65	09/66
b8(m)	23/64	27/64	18/64	9/63	05/64	11/64	06/64	17/64	03/64	1/64
The objective function (m3)	6/3356	5/3397	5/3431	6/3396	4/3400	6/3387	3396	8/3386	1/3393	3353

In Figures (5) and (6), the dimensions of the Koyna weight concrete dam and the volume of concrete used in the existing and optimal sections are compared, respectively.

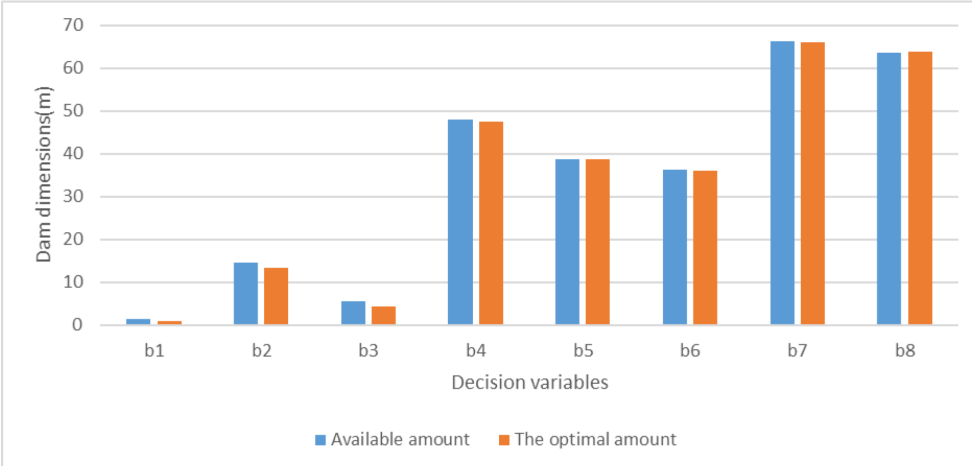

Fig. 5. Comparison of Koyna concrete weight barrier dimensions in existing and optimal conditions (meters).

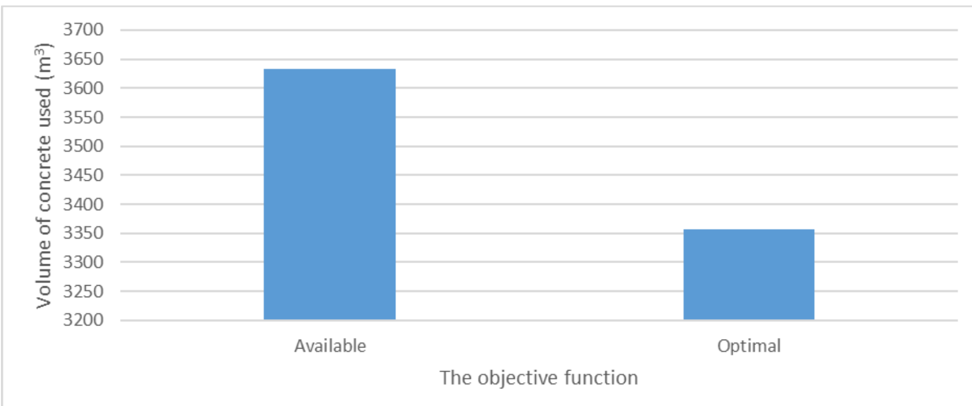

Fig. 6. The volume of concrete used in constructing Koyna Dam in the existing and optimal condition (cubic meters).

After calculating the optimal dimensions of the dam, the reliability coefficient against overturning and slipping, and stress on the surface of the dam body was also calculated, the results of which are presented in Table (4).

Table 4
Stress analysis and stability parameters in the existing and optimal Koyna weighted concrete dam condition.

Extraordinary loading	σ_U	**SFF**	**S_F**
In the current state	39/90	58/1	64/1
In optimal mode	45/129	54/1	52/1

In Table (4), SF is the roll-over reliability coefficient, SFF is the slip reliability coefficient, σ_U According to the mentioned standards, Koyna weighted concrete dam with optimized dimensions with the invasive weed optimization algorithm. is the stress at the dam body level. The presented results show that the amount of problem constraints after optimization has appropriate and reliable values. It remains stable against various forces.

11. Conclusions

As a result of the use of optimal parameters in this issue, the design's accuracy is significantly improved as well as the dimensions are selected in a way that reduces the quantity of concrete used in the dam's construction. Based on the available parameters and optimal parameters obtained using the invasive weed optimization method, the objective function of the Koyna weight concrete dam is 3633 cubic meters and 3353 cubic meters, respectively. As a result of the optimal parameters, the objective function has been reduced by 7.7% in comparison with the existing parameters. The results also show that in the 150th seed and 10 times of program execution, the objective function converges to the optimal function. As a result, the invasive weed optimization model rapidly converges to the optimal response.

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Conflicts of interest

The authors declare no conflict of interest.

Authors contribution statement

M.A.M., M.K., V.G.: Conceptualization; M.A.M.: Data curation; M.A.M. and V.G.: Formal analysis; M.A.M., V.G.: Investigation; M.A.M., V.G.: Methodology; V.G.: Project administration; V.G.: Resources; M.A.M.: Software; V.G.: Supervision; M.A.M. and V.G.: Validation; M.A.M. and V.G.: Visualization; V.G.: Roles/Writing – original draft; V.G.: Writing – review & editing.

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