

LINKED SIMULATION-OPTIMIZATION MODEL FOR OPTIMUM HYDRAULIC DESIGN OF WATER RETAINING STRUCTURES CONSTRUCTED ON PERMEABLE SOILS

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ABSTRACT: Hydraulic Water Retaining Structures (HWRS), such as dams, weirs and regulators are important projects and necessary for water management. Seepage analysis results under HWRS substantially influences the design of HWRS. One of the biggest challenges in design of HWRS is to determine the accurate seepage characteristics with complex flow conditions, and simultaneously to find the optimum design considering safety and cost. Therefore, this study concentrates on developing a linked simulation-optimization (S-O) model for complex flow conditions. This is achieved via linking the numerical seepage simulation (Geo-Studio/SEEPW) with the Genetic Algorithm (GA) evolutionary optimization solver. Since, a direct linking of numerical model with optimization model is computationally expensive and time consuming, well-trained Support vector machine (SVM) surrogate models are linked to the optimization model instead of a numerical model within the S-O model. The seepage characteristics of optimum design obtained by S-O are evaluated for accuracy by comparing these with the numerical seepage modelling (SEEPW) solutions. The comparison, in general, shows good agreements. Accordingly, the S-O methodology is potentially applicable for providing safe, efficient and economical design of HWRS constructed on a complex seepage flow domain.

Keywords: Support vector machine, Genetic algorithm, Seepage modeling, Hydraulic structures design

1. INTRODUCTION

Construction of Hydraulic Water Retaining Structures (HWRS) is the strategic aim for most communities around the world in order to build a strong water management system. Seepage analysis related to HWRS is a critical step of HWRS design [1]. In addition to the direct impacts of hydrostatic water pressures on the structural system of the HWRS, the seepage design parameters such as uplift pressures, and exit gradient are the other fundamental factors needed to be incorporated in HWRS design.

The earliest theories and methods, such as Bligh's creep theory, Lane's weighted creep theory, Flow-net method, fragment method and Khosla's theory [1] utilized to analyse seepage related to HWRS involve many simplifications and are based on many empirical assumptions. These methods are applicable only for simple, symmetrical cases and quite general soil conditions (homogeneous and isotropic), which are rarely found in the real field [2]. Moreover, the solutions of these methods are approximation solutions, and these generally display noticeable error compared with experimental observations and the numerical solutions [3].

In contrast, the numerical seepage analysis methods such as the finite element method (FEM) provides accurate solutions for a wide range of the seepage problems encountered in the real field [4, 5]. However, these solutions might not be useful, as the resulting designs may not satisfy the safety requirements and also would not optimize the construction costs. Therefore, utilizing an optimization technique could provide a

reliable and optimum solution, especially when accurate numerical seepage simulation responses are integrated in the optimization model. Accordingly, based on linked simulation-optimization S-O methodology [6-8], an ideal HWRS design could be achieved. This methodology involves developing a constrained optimization model using Genetic Algorithm (GA) integrating all design safety factors regarding the wide range of applied forces, i. e., hydrostatic pressure, uplift pressure, exit gradient, and considering, the minimum cost as the objective function of the optimization model.

The developed optimization model must be linked with the numerical seepage analysis model to concurrently evaluate the candidate designs (solutions) of the HWRS. However, the direct linking of optimization model with the numerical seepage model is a computationally demanding and time consuming task. This is because the GA calls the simulation model numerous times to evaluate the objective function and the constraints, which might need long computation time even with high speed processors. Alternatively, machine learning technique is used to build a well-trained model (surrogate model), which could be efficiently used instead of the numerical model. A well trained surrogate model can expeditiously and accurately predict the responses of the numerical model for complex problems within the linked S-O model.

Many machine learning techniques could be used in building the surrogate models, such as artificial neural network (ANN), fuzzy logic (FL), multivariate adaptive regression splines (MARS), genetic programming (GP) and support vector machine (SVM). The SVM is

selected for this study, because SVM is considered a powerful deep-learning tool. SVM is utilized in the classification, function approximation and prediction by which a nonlinear and complex engineering problems can be efficiently modeled. Moreover, in addition to the efficiency and predictive accuracy, SVM has a generalization ability to accurately predict the responses even for data out of the training range. Additionally, SVM can overcome the noisy data in the training phase by integrating the most governing support vectors (training data). Hence, SVM has the ability to overcome the over-training phenomena [9].

Recently, SVM has been utilized to model complex civil engineering problems to provide an extensive understanding of the variables involved in the model [9-16]. In the majority of the conducted researches, SVM is utilized to predict specific responses depending on the input variables or to simulate performance of a particular engineering system with special conditions. For example, in hydraulic structure design, SVM has been used to predict the forecasting of the tangential shift of a concrete dam [14], and to predict future dam responses with environmental variables [17]. Nonetheless, SVM has been rarely utilized as a surrogate model within the optimization model in the hydraulic structure design problems. Application of other machine learning techniques for solving optimization problems related to hydraulic structures design incorporating complex soil properties has been very limited as well.

This paper concentrates on developing a linked S-O model which is based on two different models. The first model is the constraint optimization model using GA. The objective function is the minimum construction cost of HWRS and the constraints reflect the HWRS design requirements. The second model is the surrogate model based on the SVM. The surrogate model is extensively trained using numerically simulated data generated by a numerical seepage modeling code

(Geo_Studio2012/ SEEPW) [18]. Additionally, the seepage design parameters obtained as the solution of the optimal design by the S-O model are evaluated using numerical modelling to investigate the prediction accuracy of the SVM within an S-O model.

2. NUMERICAL MODEL SOLUTION AND TRAINING DATA GENERATION

In contrast to an experimental study, the numerical model could provide accurate and quick solutions even for complex problems, especially when high speed processors are used. The optimization model incorporates the numerical responses, either obtained directly using the numerical model code or approximately by the surrogate models. As it is difficult and computationally expensive to directly link the optimization model with the numerical model, surrogate models linked to the optimization model need to be developed.

The first step in designing the surrogate model is to propose a conceptual model, as shown in Fig. (1). Based on the conceptual model, numerous sets of input data could be generated, then the numerical model is solved for each set to find the output data. The SVM models could be trained based on these data sets. The conceptual model comprises forty two input design variables, which are randomly varied within assumed ranges shown in Table (1). In this study, the proposed design variables are the dimensions and the inclination of the ten sheet piles (S_1 - S_{10}) in addition to the spacing between them. The symbols for the sheet pile depths are ($d_1, d_2 \dots d_{10}$), for the angles are ($\beta_1, \beta_2 \dots \beta_{10}$) and for the width between the sheet piles ($b_1, b_2 \dots b_{10}$). The subsoil foundation consists of three layers (DL_1, DL_2, DL_3) and their hydraulic conductivities are (k_{x1}, k_{x2}, k_{x3}) with the anisotropy ratio (K_y/K_x)₁, (K_y/K_x)₂, (K_y/K_x)₃ respectively. The total upstream water head (H) is also included in the input design variable.

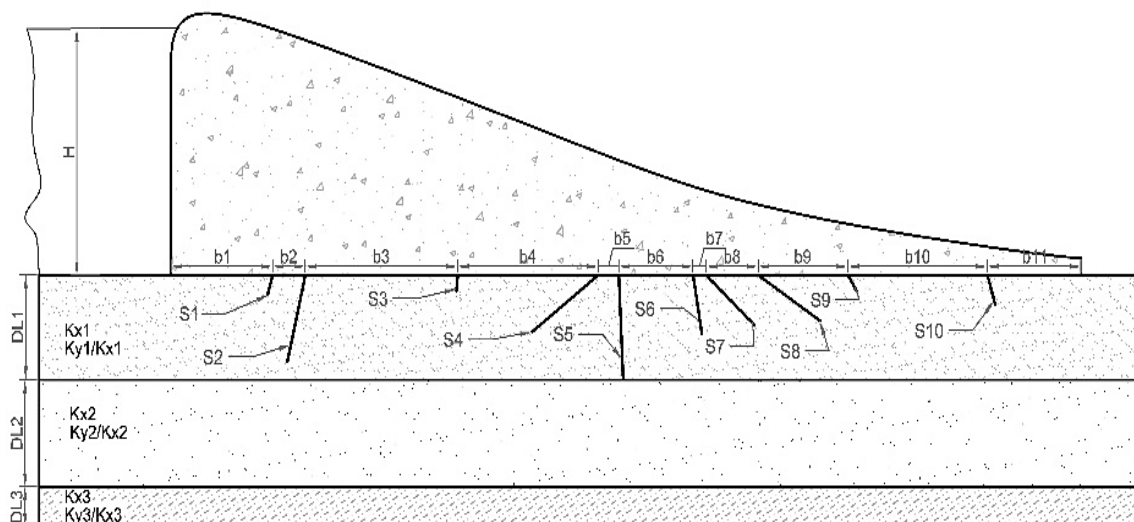


Fig. 1. Conceptual numerical model

Table 1 Input data description

Input variable	Unite	Min	Max	Avg.	Std.
b_1, b_2, \dots, b_{11}	m	1	120	60.37	34.26
d_1, d_2, \dots, d_{10}	m	0	60	29.98	17.37
$\beta_1, \beta_2, \dots, \beta_{10}$	deg.	30	150	90.4	34.11
LD1, LD2, LD3	m	5	100	53.67	27.01
kx_1, kx_2, kx_2	m ³ /day	0.01	20	10.04	5.78
Anisotropy ratio(Ky/Kx)	-	0.1	1.5	0.80	0.40

Each input data set is used to solve the numerical model to obtain the output data sets. Some of the input design variables can be considered as the decision variables in the optimization model to find the best variable values, and the ideal combinations of these variables which provide the optimum solution for the HWRS.

All the input sets (1700 sets) are randomly generated using Latin hypercube sampling method (LHS). LHS provides a uniform periodic random data by which robust training could be achieved in the machine learning process [19]. Each set of input data represents one scenario of the HWRS design. The numerical modeling code is utilized to find the resulting seepage characteristics for each scenario. The seepage characteristics include the uplift pressure in front (PE_i) and behind (PC_i) each single sheet pile in addition to the exit gradient at the end of the floor of hydraulic structure (toe). The seepage characteristics resulting from the numerical seepage modeling represent the output data, which could be utilized with the input data to train the SVM models.

3. SUPPORT VECTOR MACHINE

Support vector machine is a deep learning technique used for classification and regression problems. Recently, SVM has been implemented in wide academic applications and engineering problems because the SVM has a good generalization ability, and is less impacted by overfitting phenomena. Generally, the SVM algorithm selects from the training data the best hyperplane (vector) which provides an efficient classification. The SVM algorithm maximizes the distance between the center of the hyperplane and its boundary (margin) to attain the best SVM model. Therefore, the ideal SVM must have wider margins, then the SVM model could provide accurate prediction and high generalization ability [20, 21].

The SVM technique is applied to build the models that could accurately predict the numerical responses. Matlab programming language is utilized to develop the SVM models, because Matlab is a versatile tool and provides many options that can be modified to build perfect SVM models. 1700 sets of the simulated data obtained by solving the numerical code are used to train and build the SVM models. Twenty one models are built to determine the uplift pressure in front and behind each sheet pile, and the exit gradient value near the end

of the HWRS. The SVM is trained on the simulated data where 90% of the data is utilized for training and 10% are used for testing. The coefficient of determination (RSQ) and mean square error (MSE) for the training and testing phases are listed in the Table (2).

The parameter for each SVM model are carefully selected after several iterations of trial and errors until best RSQ and smaller MSE are achieved. It could be concluded that the most influencing parameter on SVM performance is the kernel function type, and the constraint box. The kernel function used in this study is the polynomial kernel with varied order, which provide precise prediction compared to the other kernels.

Table 2 Developed SVM models attributes

Model	RSQ TRAIN	MSE TRAIN	RSQ TEST	MSE TEST
Exit gradient	0.95	0.1	0.91	0.17
PC10	0.97	1.22	0.97	1.08
PE10	0.96	4.57	0.97	3.64
PC9	0.95	7.66	0.95	6.35
PE9	0.99	1.32	0.99	0.96
PC8	0.98	3.74	0.98	2.93
PE8	0.99	0.82	0.99	0.97
PC7	0.99	2.12	0.99	1.59
PE7	0.98	5.25	0.99	0.77
PC6	0.99	1.74	0.99	1.46
PE6	0.99	1.08	0.99	0.65
PC5	0.99	0.99	0.99	1.13
PE5	0.99	0.63	0.99	0.54
PC4	0.99	1.21	0.99	1.2
PE4	0.99	0.77	0.99	0.74
PC3	0.99	0.95	0.99	0.94
PE3	0.99	0.94	0.99	0.93
PC2	0.99	1.92	0.99	1.94
PE2	0.99	1.11	0.99	1.13
PC1	0.99	2.75	0.99	3.2
PE1	0.99	3.2	0.99	2.8

4. OPTIMIZATION MODEL

The constrained optimization model within the S-O model is formulated to find the best design of HWRS at a minimum cost. Because of the complexity of the optimization task, the GA is used in this study. GA evaluates the fitness value and the constraints based on the surrogate model responses. Additionally, GA is likely to provide a global optimum solution and has the ability to deal with a complex problem as it does not rely on differentiating the performance equations to find the optimum solution. Instead GA is based on a natural selection principle [22, 23]. The GA is efficient in finding the global solution in such a problem, where the performance function is based on the surrogate model responses. In the S-O model, GA calls the surrogate models (SVM) huge number of times to evaluate the fitness value and the constraints for each candidate solution (individual) presented by GA until the optimum design is achieved. Matlab programming language is used to implement the optimization model. The GA parameters specified in this study are: Population Size 2000, Elite Count 10, Crossover Fraction 0.8, Function Tolerance 1e-6, Constraint

Tolerance $1e-3$, and the rest of GA options are left to default Matlab options.

The decision vector (X) involved in the optimization model represents the most important design variables of the proposed HWRS model (conceptual model). The X is modified many times by GA to find the minimum construction cost of the design, and simultaneously to provide safe design that satisfies all design requirements (constraints).

The decision vector is listed, as shown below, where the design variables from x_1 to x_{11} represent the width between sheet piles (b_1, b_2, \dots, b_{11}), variables from x_{12} to x_{22} represent the depth of the sheet piles (d_1, d_2, \dots, d_{10}) the variables from x_{23} to x_{32} represent the inclination angle for the sheet piles ($\beta_1, \beta_2, \dots, \beta_{10}$). The optimization problem is formulated, as shown below:

$$\text{Find } X = \begin{pmatrix} x_1 \\ x_2 \\ \cdot \\ \cdot \\ \cdot \\ \cdot \\ \cdot \\ \cdot \\ \cdot \\ \cdot \\ x_{32} \end{pmatrix} = \begin{pmatrix} b_1 \\ b_2 \\ \cdot \\ \cdot \\ \cdot \\ b_{11} \\ d_1 \\ d_2 \\ \cdot \\ \cdot \\ \cdot \\ d_{10} \\ \beta_1 \\ \beta_2 \\ \cdot \\ \cdot \\ \cdot \\ \beta_{10} \end{pmatrix}$$

Which minimizes the objective function shown in Eq.(1)

$$\text{Minimize: } f(X) = c_f \sum_{x=1}^{11} T_i x_i + c_c t_c \sum_{x=12}^{21} x_i \quad (1)$$

Where: T_i represents the average thickness of the floor between two sheet piles, c_f = The cost of constructing the body of the HWRS per cubic meter (\$500/m³), c_c = The construction cost of the sheet pile per cubic meter (\$1000/m³), t_c = the thickness of the sheet pile, which is constant = 0.5m .

The decision vector is subjected to the following constraints:

Flotation constraints: The uplift pressure influence on the HWRS at the specific location must be less than the counterbalanced weight of the HWRS cross section at that location [24, 25]. Therefore, the value PC and PE for each sheet pile must be sufficiently counterbalanced by the floor thickness at these points. The safety factor assumed is 1.3, as shown in Eq. (2).

$$t_i \geq 1.3 \left(\frac{PE_i \text{ or } PC_i}{G_c - 1} \right), i = 1, 2, 3, \dots, 20 \quad (2)$$

Where G_c is the specific gravity of the concrete (construction material).

The exit gradient constrain: If the exit gradient is equal or more than the critical gradient, piping failure is likely. Therefore, it is recommended that the exit gradient value must be at least 3 to 5 times less than critical gradient [26, 27]

Usually, the shortest stream line or the closest point of HWRS toe is the most critical point at which the largest value of exit gradient could be seen. Therefore, this point selected at the toe of HWRS and near the soil surface. The safety factor of exit gradient is determined by Eq. (3)

$$F.S = \frac{i_c}{i_e} \quad (3)$$

Where i_c is critical exit gradient and given by Eq. (4)

$$i_c = \frac{\gamma_{sub}}{\gamma_w} \quad (4)$$

Where γ_{sub} is the submerged soil density, γ_w is the weight density of water. The soil properties are considered mixed grained sand, which has $\gamma_{sat} = 21.2$ kN/m³ and that results in $icr = 1.15$ [28].

Other constraints: Many other constraints are also considered in the optimization model, such as sliding constraint and overturning constraint with safety factor more than 1.5. The preventing eccentric loading state constraints is incorporated also to ensure uniform distribution of the loads on the foundation surface. Hence, the resultant force, which is obtained by dividing the total momentum at the toe of HWRS by the total vertical load, must be located within the second third of the total width of HWRS [1]. Furthermore, many logical constraints and bounds are specified in the optimization model to prevent illogical solutions or negative values of the decision variables.

Additionally, it is interesting to note that the value PC and PE for each sheet pile, and i_e values involved in the S-O model are determined based on the surrogate models responses. The surrogate models within the optimization model also represent the binding constraints, where the decision vector must satisfy the simulation constraints in addition to the design constraints.

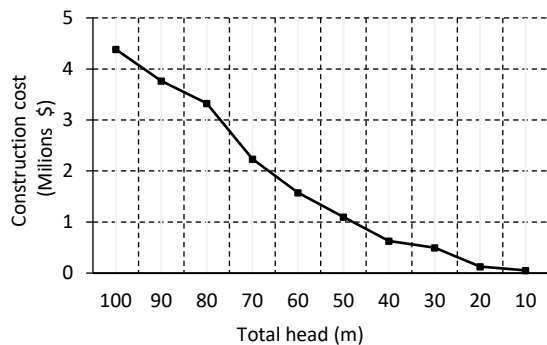
5. RESULTS AND DISCUSSION

The developed methodology was applied to find the optimum design of HWRS by optimizing the design variables of the conceptual model based on the surrogate models responses. Ten different cases having different H values starting from 10 m to 100 m were solved by S-O model. The other parameters are left constant, such as the hydraulic conductivity of each layer is 5 m/day, the anisotropy ratio is 1 and the depth of each subsoil layer is 50 m for all cases. For all implemented cases, the solution obtained by S-O model satisfy the design requirement and the safety factors, as shown in the Table (3).

Table 3 Optimum solutions safety factors for the implemented cases

Total head(m)	Exit gradient	Eccentric distance	Sliding	Overturning
100	0.23	58.6	1.76	2.40
90	0.21	55.88	1.77	2.56
80	0.21	56.7	1.827	2.945
70	0.23	42.82	1.805	2.448
60	0.23	35.11	1.791	2.354
50	0.23	28.89	1.781	2.40
40	0.23	22.1	1.767	2.051
30	0.23	24.67	1.902	3.434
20	0.23	8.914	1.671	1.844
10	0.23	10.13	1.99	3.585

The optimum cost versus corresponding head value is shown in Fig. (2). The total construction cost logically increases with the augmentation of the upstream water head. However, the slope of the curve for head value less than 40 m is smaller than when the head value is 40 m and more. For instance, the average construction cost for HWRS under head values ranging between 40 m to 10 m is 11065 \$/m, for head values ranging between 50 m to 70 m is 26749 \$/m, and for head values ranging between 80 m to 100 m is 42418 \$/m. That means, for example, the construction cost for a three HWRS having an upstream water head of 30 m is significantly cheaper than the construction cost of a single HWRS with an upstream water head of 90 m. This difference could be attributed to the dramatic increasing of the depth of the last sheet pile and the width of HWRS with large upstream water head value (see Fig. (3) & Fig. (4)).



Note: The construction cost is per meter length of HWRS

Fig.2. Optimum construction cost for different head value (H)

Generally, the contribution of the variables b_1 to b_8 and d_1 to d_8 on the safety of the HWRS is neglected, where the optimum values for these variables is almost zero, as shown in Fig. (3) and Fig. (4). Consequently, as the length of d_1 to d_8 reach their minimum value, their inclination angles become meaningless. Nonetheless, the inclination angle has a noticeable effect on reduction of uplift pressure, especially when β value is less than 90 degrees. However, when β value is more than 90 degree it has a significant effect in reduction of the exit gradient value especially for S_{10} .

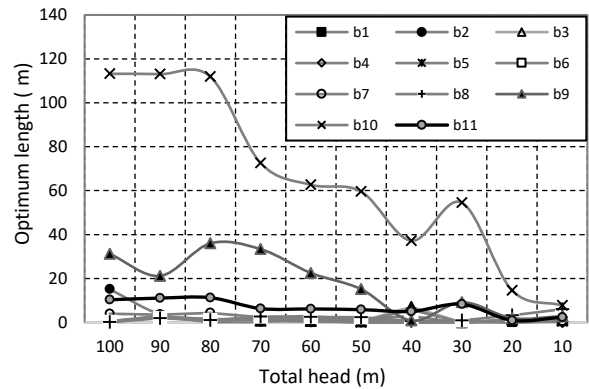


Fig. 3. Optimum construction cost for different head values (H)

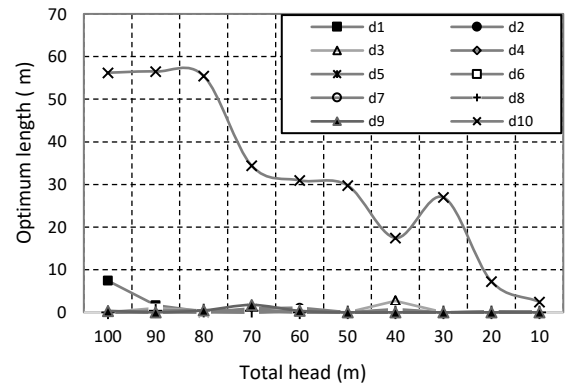


Fig. 4. Optimum construction cost for different head values (H)

However, the optimum solution obtained for each case is based more on increasing the HWRS width to reduce the uplift pressure, and less on the sheet pile lengths. This could be attributed to two reasons. First, the construction cost of the sheet piles is more expensive than the construction cost of the HWRS floor. Secondly, the uplift pressure value must be counterbalanced by the sufficient weight of the construction material of HWRS cross section. Accordingly, even if it is costly solution, it is necessary to provide a safe thickness against the uplift pressure. Furthermore, some design requirements significantly influence the design features. For example, to ensure the stability of HWRS against overturning condition, the GA increases the total width of HWRS to provide more stability against the overturning forces and the huge amount of the developed moments. Besides, preventing eccentric load state on the foundation of HWRS is another critical design requirement. Therefore, GA restricts the reaction loads resultant to be located within the second third of the total width. As a result, as shown in Fig. (5), the resultant distance (e) is located at the edge of the second third of the total width of HWRS (minimum allowable limit) to provide safe load distribution on the foundation of HWRS, and simultaneously to attain the minimum cost. Hence, the

optimum solutions satisfy all constraints and achieve cheapest HWRS construction cost.

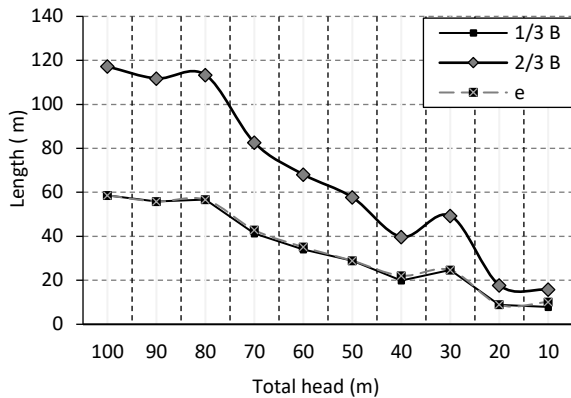


Fig.5. Location of the resultant force for the optimum solutions versus different head values (H)

On the other hand, because of the crucial impact of the exit gradient on the design of HWRS and only d_{10} has a significant control in reduction of the exit gradient value, in all optimum solutions, the d_{10} values have a considerable length, as shown in Fig. (4). Additionally, the optimum sheet pile inclination angle of β_{10} is 150 degrees toward downstream. The increase of β_{10} value effectively decreases the exit gradient value, as the streamline length of seeping water significantly increases and in consequences the exit gradient value decreases. Moreover, another factor which might affect

the exit gradient is b_{10} because increasing b_{10} reduces the uplift pressure and consequently decreases the exit gradient value.

Mainly, the exit gradient value for all cases shown in Table (3) reaches the maximum allowable value to satisfy a minimum safety factor and efficient cost. Accordingly, the exit gradient safety factor plays a critical role in the selection of optimal decision variable values in the optimization process.

Finally, an extensive evaluation was conducted for validating the S-O solutions. The seepage design variables (PE_i , PC_i , exit gradient) were evaluated by solving the optimum solutions using numerical modelling, then compared the seepage characteristic obtained by numerical solution with the same values obtained from the S-O model. In general, the evaluation results showed that the maximum percentage of error between the S-O model and numerical solutions is not more than $10 (\pm 5) \%$, as shown in Fig (6) to Fig. (11). This figure demonstrates that the SVM generalization ability with unseen and extreme data is highly accepted. However, the error percentages for the predicted exit gradient values are larger than the predicted uplift pressure values. This could be attributed to the large number of the input variables integrated in the exit gradient surrogate model. Additionally, the relationship between input data and the predicted exit gradient value is more complex. Nonetheless, the exit gradient safety factors for the optimum solutions are still within the standard and safe limit (3-5).

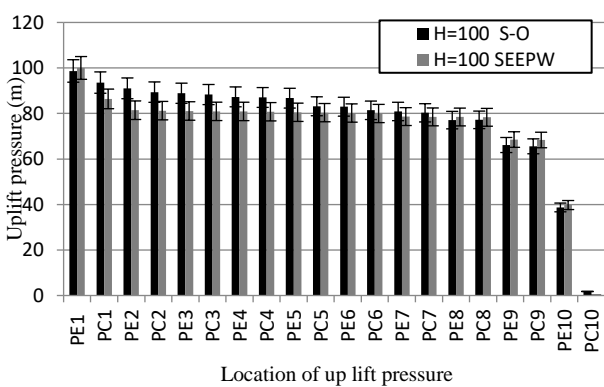


Fig. 6. Evaluation the optimum design uplift pressure in different locations H=100

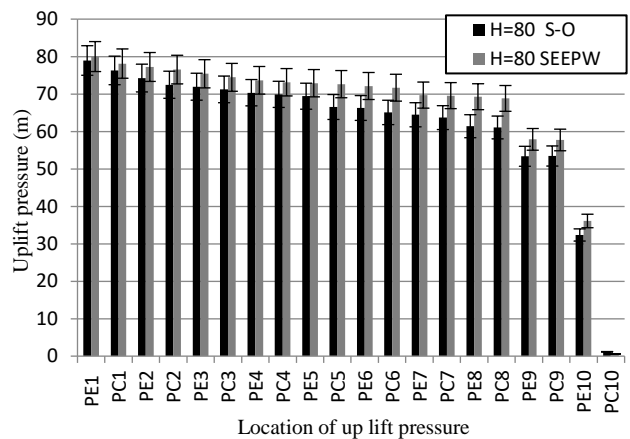


Fig. 7. Evaluation the optimum design uplift pressure in different locations H=80

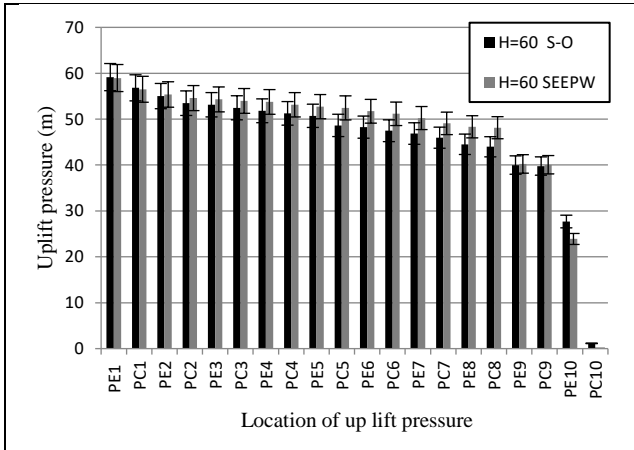


Fig. 8. Evaluation the optimum design uplift pressure in different locations H=60

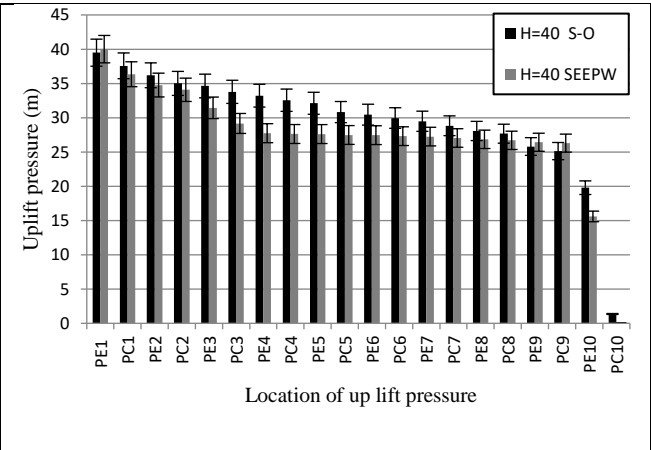


Fig. 9. Evaluation the optimum design uplift pressure in different locations H=40

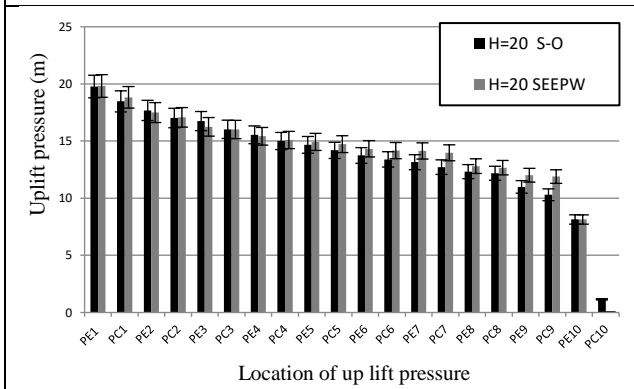


Fig. 10. Evaluation the optimum design uplift pressure in different locations H=20

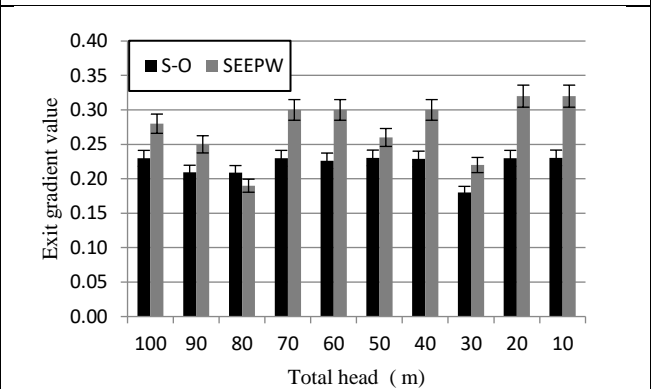


Fig. 11. Evaluation the optimum design exit gradient value for different head values

6. CONCLUSION

The optimization based searching process is an expensive and computationally demanding task, especially when the optimization model is linked to a numerical simulation model to evaluate the fitness value and the constraints. Therefore, the linked S-O model based on SVM surrogate models was successfully and efficiently implemented to find the optimum design of HWRs. Many well trained SVM surrogate models imitating numerical seepage modelling responses were built to predict the seepage characteristics under HWRs. Based on the accurate responses of the surrogate models, GA evaluated the fitness value and the constraints. Therefore, a reliable and optimum design of HWRs was achieved.

The seepage design variable values (PE_i, PC_i, exit gradient) obtained as optimum solutions were validated using numerical solutions. The validation process showed that the surrogate model predictions accurately matched the numerical solutions, even for unseen or extreme scenarios representing the optimum solutions.

In general, the construction cost of HWRs dramatically increases with the upstream water head augmentation from 11065\$/m for head values less than 40 m to 42418 \$/m for head values around 100 m. The optimum and safe hydraulic design of HWRs must include a sufficient floor width (more than H value) and a sufficient length for the last sheet pile (not less than 0.5H), with inclination angle attaining up to 150 degrees. All the HWRs design requirements and safety factors are satisfied for all implemented cases.

Finally the methodology is potentially applicable to find the optimum design of HWRs at minimum cost for different scenarios, within the specified training data range. Future studies could be dedicated to explore the effect the soil properties on the optimum design of HWRs utilizing different machine learning techniques and optimization solvers which can attain more accurate and reliable design.

7. REFERENCES

1. Garg, S.K., Irrigation engineering and hydraulic structures. 1987: Khanna publishers.
2. Lambe, T.W. and R.V. Whitman. Soil mechanics SI version. 2008: John Wiley & Sons.
3. Shahrbanozadeh, M., G.-A. Barani, and S. Shojaee, Simulation of flow through dam foundation by isogeometric method. Engineering Science and Technology, an International Journal, 2015. **18**(2): p. 185-193.
4. Mansuri, B., F. Salmasi, and B. Oghati, Effect of Location and Angle of Cutoff Wall on Uplift Pressure in Diversion Dam. Geotechnical and Geological Engineering, 2014. **32**(5): p. 1165-1173.
5. Moharrami, A., et al., Performance of Cutoff Walls Under Hydraulic Structures Against Uplift Pressure and Piping Phenomenon. Geotechnical and Geological Engineering, 2014. **33**(1): p. 95-103.
6. Al-Juboori, M. and B. Datta, Artificial Neural Network Modeling and Genetic Algorithm Based Optimization of Hydraulic Design Related to Seepage under Concrete Gravity Dams on Permeable Soils. 2017.
7. Sreekanth, J. and B. Datta, Review: simulation-optimization models for the management and monitoring of coastal aquifers. Hydrogeology Journal, 2015. **23**(6): p. 1155-1166.
8. Prakash, O. and B. Datta, Optimal monitoring network design for efficient identification of unknown groundwater pollution sources. Int. J. of GEOMATE, 2014. **6**(1): p. 785-790.
9. Deka, P.C., Support vector machine applications in the field of hydrology: a review. Applied Soft Computing, 2014. **19**: p. 372-386.
10. Fisher, W.D., T.K. Camp, and V.V. Krzhizhanovskaya, Anomaly detection in earth dam and levee passive seismic data using support vector machines and automatic feature selection. Journal of Computational Science, 2016.
11. Mahani, A.S., et al., Hybridizing two-stage meta-heuristic optimization model with weighted least squares support vector machine for optimal shape of double-arch dams. Applied Soft Computing, 2015. **27**: p. 205-218.
12. Pal, M., N. Singh, and N. Tiwari, Support vector regression based modeling of pier scour using field data. Engineering Applications of Artificial Intelligence, 2011. **24**(5): p. 911-916.
13. Parsaie, A., H.A. Yonesi, and S. Najafian, Predictive modeling of discharge in compound open channel by support vector machine technique. Modeling Earth Systems and Environment, 2015. **1**(1-2): p. 1-6.
14. Ranković, V., et al., Development of support vector regression identification model for prediction of dam structural behaviour. Structural Safety, 2014. **48**: p. 33-39.
15. Su, H., Z. Chen, and Z. Wen, Performance improvement method of support vector machine-based model monitoring dam safety. Structural Control and Health Monitoring, 2016. **23**(2): p. 252-266.
16. Yu, P.-S., S.-T. Chen, and I.-F. Chang, Support vector regression for real-time flood stage forecasting. Journal of Hydrology, 2006. **328**(3): p. 704-716.
17. Cheng, L. and D. Zheng, Two online dam safety monitoring models based on the process of extracting environmental effect. Advances in Engineering Software, 2013. **57**: p. 48-56.
18. Krahn, J., Seepage modeling with SEEP/W: An engineering methodology. GEO-SLOPE International Ltd. Calgary, Alberta, Canada, 2004.
19. Cox, D.R. and N. Reid, The theory of the design of experiments. 2000: CRC Press.
20. Kramer, O., Machine Learning in Evolution Strategies. Vol. 20. 2016: Springer.
21. Alpaydin, E., Introduction to machine learning. 2014: MIT press.
22. Gen, M. and R. Cheng, Genetic algorithm and engineering optimization. John Wiley and Sons, New York, 2000.
23. Haupt, R.L. and S.E. Haupt, Practical genetic algorithms. 2004: John Wiley & Sons.
24. U.S. Army Corps of Engineers, Reliability analysis and risk assessment for seepage and slope stability failure modes for embankment dams 2006.
25. Bligh, W.G., Dams and Weirs: An Analytical and Practical Treatise on Gravity Dams and Weirs; Arch and Buttress Dams; Submerged Weirs; and Barrages. 1915: American Technical Society.
26. Harr, M.E., Groundwater and seepage. 2012: Courier Corporation.
27. Khosla, A.N., N.K. Bose, and E.M. Taylor, Design of weirs on permeable foundations. 1936.
28. Terzaghi, K., R.B. Peck, and G. Mesri, Soil mechanics in engineering practice. 1996: John Wiley & Sons.

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