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Multi-Objective Design of a Horizontal Flow Subsurface Wetland

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Abstract: An artificial wetland is used to treat gray, waste, storm or industrial water. This is an engineering system that uses natural functions of vegetation, soil and organisms to provide secondary treatment to gray water. In the physical design of each artificial wetland, there are various action factors that must meet certain characteristics so that the level of gray-water pollution is reduced. In this sense, several design methodologies have been developed and reported in the literature, but some are customized designs and often do not meet the required decontamination objectives. This challenge increases as the complexity of the task in its structure also increases. Particularly in this work, a multi-objective evolutionary algorithm is used to optimize the physical design of a horizontal flow subsurface wetland (HFSW) for gray-water treatment. The study aims to achieve two objectives: first, to minimize the physical volume, and second, to maximize the contaminant removal efficiency. The defined objective functions depend on six design variables called hydraulic retention time, width, length, water depth inside the wetland, substrate depth and slope. Three constraint functions are also defined: removal efficiency greater than 95%, physical volume below 500 m^3 and compliance with a length–width ratio is 3:1, varying the population size and number of generations equal to 200, 400, and 600. The set of solutions according to the number of generations as well as the Pareto front corresponds to the best solution that complies with the constraints of the problem of oversizing the HFSW, and the Pareto front shows the interaction between the objectives and their behavior, reflecting the problem's nature as minimization–maximization.

Keywords: multi-objective optimization; wetland; water quality; nature-based solutions

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1. Introduction

Pollution aggravates various environmental problems such as water scarcity, soil erosion and atmospheric drought. The treatment of water resources is increasingly important, and wastewater treatment processes are sought to be efficient and effective [1]. On the one hand, green technologies are still developing to provide sustainable solutions to the problems of pollution. On the other hand, constructed wetlands technology is an established green multi-purpose option for water management and wastewater treatment, with numerous effectively proven applications worldwide and with multiple environmental and economic advantages. These systems can operate as water treatment plants, habitat creation sites, urban wildlife refuges, recreational or educational facilities, landscape engineering and ecological art areas [1–3]. Note that conventional wastewater treatment systems are less efficient in removing recalcitrant compounds and color. In response to this problem, constructed wetlands could be one option for domestic and industrial wastewater treatment [4,5] since these systems are simple and have proved to be sustainable and green technology to improve wastewater quality [2]. However, despite its simplicity, this is a multi-objective optimization problem [3,6,7]. In this way, Ikenberry et al. [8] addressed the problem of groundwater wastewater in Murdoc, Nebraska, by implementing a surface flow constructed wetland (SFW). The main target of this paper was to optimize the carbon tetrachloride remediation process, while safeguarding adjacent properties from potential flooding and channel instability. However, in order to increase the biodiversity of the SFW, deeper excavations were carried out, resulting in the configuration of a bottom with undulating characteristics. This last particularity caused an increase in the hydraulic retention time and, therefore, in the sizing of the SFW. Huang et al. [9] used the SubWet 2.0 numerical model to model and analyze the treatment efficiency of vertical flow constructed wetlands. The SubWet 2.0 model uses, as design input values, the width, length, depth, precipitation factor, slope, average percentage of wetland particles, hydraulic conductivity and flow, in addition to specifying the type of natural or artificial wetland. Once the parameters are established, the model computes the area, volume, hydraulic head, recommended horizontal flow, recommended flow, flow width and number of channels. Further, it is capable of simulating the elimination of biochemical oxygen demand (BOD_5), ammonium nitrogen, nitrate nitrogen and total phosphorus (TP). To evaluate the modeling performance, in terms of these pollutants, use the correlation coefficient and the Nash–Sutcliffe efficiency coefficient. However, it only provides one design for each simulated wetland without applying optimization techniques for area reduction. Furthermore, the simulation start parameters are fixed, which does not allow exploring other designs. As a consequence, the simulation time is conditioned by the input data, which can cause very fast or very slow simulations. Andreo et al. [10], examines the removal efficiency of five pollutants: BOD_5, TP, chemical oxygen demand, total suspended solids and total nitrogen in a horizontal flow subsurface wetland (HFSW). Since the HFSW experiences bed drying problems due to oversizing and high evapotranspiration in the area, a theoretical resizing of the HFSW is proposed using the Reed model. However, although the input data for optimization are obtained in the field, which increases the reliability, the Reed model only provides a single design, which must be adjusted only to the initial operating conditions of the HFSW, limiting thus the exploration of new design proposals. Liao et al. [11] reported the study of one of the main drainage channels of Beijing, which is the Beiyun River in China, where 76% of the city's total wastewater is discharged into this river. To improve the ecological environment and water quality of the river, an artificial wetland was designed and built in the lower part of the river. In the evaluation and optimization process, the MIKE 21 modeling system was used to simulate the water distribution system. Furthermore, a back-propagation neural network was trained to quantify the relationship between hydrological parameters and the overall performance of the constructed wetland based on its water distribution characteristics and their corresponding scores. A genetic algorithm was used for optimizing the water control, which determines an optimal strategy that combines the flow and water level parameters of the artificial wetland. Water quality was simulated by applying chemical oxygen demand as a pollutant index to reflect the water quality of the surface flow zone with an estimated initial concentration of 25.6 mg/L. Despite the complexity of the simulation and optimization process, which involved the use of three different software's, the study lacked the graphical presentation of the generations carried out to visualize all the solutions. Likewise, an approximate simulation time of 24 h was reported, which highlights the need to consider temporal aspects in this type of analysis.

As can be seen in the papers reported to date [4,5,8–12], all artificial wetlands, designed and some already built, use different design methodologies, but none of them address the problem from a multi-objective optimization approach. This is a serious drawback since the structure of said artificial wetland differs substantially from reality. For these reasons, some artificial wetlands not only consume many financial resources during their construction and maintenance but also do not ensure that wastewater treatment is the most effective. In fact, several artificial wetlands are inoperative when their capacities are exceeded, and this is due to incorrect design planning. As a consequence, its repair is more expensive than the construction of a new artificial wetland but now considering the new challenges. Note that this process follows a trial-and-error design methodology, increasing construction costs, which is not viable from an economic point of view. With this in mind, this paper presents the use of the NSGA-II algorithm to optimize the design of an HFSW for gray-water treatment. In particular, two objectives are optimized: the minimization of the physical volume (V_F) and the maximization of the contaminant removal efficiency (μ). Hence, the design of the HFSW is formulated as a multi-objective optimization problem. The Pareto front generated by the two targets is very similar to that reported in the literature, showing the effectiveness of the optimizer. As an example, a Pareto front solution is selected, and as a consequence, the numerical value of the HFSW design variables is obtained. The NSGA-II algorithm can play a crucial role in the built wetland, providing tools for data-driven decision making and implementing sustainable management practices and strategy to the peculiarities of the HFSW. The manuscript is organized as follows: Section 2 describes the behavior equations of the HFSW. The objective functions, constraints and the search space are also defined. A flowchart of the operation of NSGA-II algorithm is briefly described in Section 3. Numerical results are discussed in Section 4, showing the generated Pareto front by the two objectives defined above. By selecting a point on the generated Pareto front, the design variables can be automatically obtained with the target of building the HFSW a posteriori. Section 5 presents a brief discussion about the multi-objective optimization of the HFSW. Finally, the conclusions are summarized in Section 6.

2. HFSW Behavior Model

A detailed description of the method used for optimizing a HFSW, from mathematical modeling, is here described. The design of the HFSW is optimized using the NSGA-II algorithm, based on the adequate selection of equations that describe the behavior of the HFSW to subsequently define the objectives, constraints and design variables. Thus, the goal is to minimize V_F and maximize μ simultaneously.

2.1. Behavior Equations

The design of artificial HFSW involves two stages. The first stage entails kinetic design, and a first-order model is given by [12,13]

$$C_s = C_e e^{-K_T t} \tag{1}$$

where K_T is the first-order kinetic constant [d^{-1}], C_e [mg/L] and C_s [mg/L] are the input–output concentrations of the pollutant, respectively, and t is the hydraulic retention time [d]. The second stage involves hydraulic design, which takes into account the superface area (A_s) [m^2] given by

$$A_s = \frac{Q ln\left(\frac{C_e}{C_s}\right)}{K_T h_m n} \tag{2}$$

where Q is the flow rate [m^3/d], h_m is the substrate depth [m] and n is the porosity. The width (W) [m] can be approximated as

$$W = \frac{1}{h_a}\left(\frac{QA_s}{sK_s}\right)^{0.5} \tag{3}$$

where h_a is the water depth [m], s is the slope [%] and K_s is the hydraulic conductivity [m/d]. The length (L) [m] is approximated as

$$L = \frac{A_s}{W} \tag{4}$$

2.2. Objective Functions

On the one hand, a drawback in the construction of artificial HFSW is that they require large areas [4,5], consuming many financial resources during their construction and maintenance, and they do not ensure that the wastewater treatment is effective. On the other hand, in the multi-objective optimization process, the objective functions to be optimized must meet two main characteristics: firstly, the objectives depend on the design variables and satisfy the design constraints; secondly, there is a trade-off between them [14]. With this in mind and from (1)–(4), the targets are defined as

$$V_F = LW(h_a + h_m) \tag{5}$$

$$\mu = 1 - e^{-K_T t} \tag{6}$$

Therefore , this study aims to minimize V_F [m^3] while maximizing μ [%] at the outlet of the HFSW and satisfying all required constraints.

2.3. Design Variables and Constraints

2.3.1. Design Variables

In a multi-objective optimization problem, the design variables, also called decision variables, have an impact on the solution of the optimization problem since during the optimization process, one must find the best combination of design variables that optimizes the designer's preference and maintains certain requirements or constraints. In this sense, Table 1 shows the design variables to be used during the optimization process along with the range of values according to the literature [15–17]. Note that the behavior of the two objective functions given by (5) and (6) depends on the design variables. However, to improve the search for solutions, in this work, the search space is expanded, and this is achieved by expanding the range of each design variable. The range of each design variable is deduced by experimentation. It is worth mentioning that the value of n and K_s are obtained from [13,16].

Table 1. Design variables.

Design Variable	Literature	This Work	Units
t	4–15 [1], 2–7 [2,3]	1–60	d
W	1–61 [2]	20–100	m
L	1–15 [2]	20–100	m
h_m	0.46–0.76 [1], 0.5–0.6 [2]	0.7–10	m
h_a	0.061–0.3 [1], 0.4–0.5 [2]	0.1–0.8	m
s	0.5–1 [1]	0–1	%

Note(s): [1] [15], [2] [16], [3] [17]. Here d means "days" and m means "meters".

2.3.2. Constraints

An objective function cannot be optimized infinitely since its performance is often limited by the presence of constraints. Thus, a constraint function is also expressed mathematically in terms of design variables. Basically, a constraint function can be an inequality or equality constraint. For this work, three constraints are defined: the first must ensure the contaminant removal with 95% efficiency. The second refers to obtaining an optimized physical volume less than 500 m^3. The third constraint must satisfy the relation of 3:1 between L and W [13,16]. Thus, the constraint functions are defined as

$$\mu \geq 0.95 \;\; (equivalent\ to\ 95\%) \tag{7}$$

$$V_F < 500 \tag{8}$$

$$\frac{L}{W} = 3:1 \tag{9}$$

3. Multi-Objective HFSW Design Methodology

On the one hand, a multi-objective optimization problem can mathematically be formulated as

$$
\begin{aligned}
min./max.\ \mathbf{f}(\mathbf{x}) &= [f_1(\mathbf{x}), f_2(\mathbf{x}), \ldots, f_n(\mathbf{x})] \\
subject\ to\ \mathbf{c}(\mathbf{x}) &= [c_1(\mathbf{x}), c_2(\mathbf{x}), \ldots, c_k(\mathbf{x})] \geq 0 \\
with \quad \mathbf{x} &= (x_1, x_2, \ldots, x_q) \in X \\
x_q^l \leq x_q &\leq x_q^u
\end{aligned}
\tag{10}
$$

where $\mathbf{f}(\mathbf{x})$ is the vector with n objective functions, $\mathbf{c}(\mathbf{x})$ is the vector with k constraint functions, and $\mathbf{x}$ is the vector with q design variables on the decision space X, limiting each design variable between the lower (x_q^l) and upper (x_q^u) limits. On the other hand, the NSGA-II method is a powerful decision space exploration engine based on genetic algorithms for solving multi-objective optimization problems as described by (10) in general and the use of (5)–(9) and the design variables of Table 1 in particular. The NSGA-II operates under four main principles: non-dominated sorting, elite preserving operator, crowding distance and selection operator. Under these principles, the NSGA-II algorithm executes the search for the best solutions of the HFSW design according to the design variables, taking a population of parents. This population undergoes an operational cycle, where individuals are adjusted within the problem's constraints. Once the solutions are found, they are appended according to the number of generations until forming an optimal set and satisfying the problem's solutions. The results of the design variables found by NSGA-II are attached to the last computed generation, forming the non-dominated solutions. The behavior of this set of solutions is verified by confronting the objectives and comparing the maximization–minimization result to form the Pareto front [18]. Since NSGA-II is coded to minimize objective functions, any objective function can easily be converted to a maximization problem by multiplying the objective function by -1. Figure 1 shows a flowchart for the execution of the algorithm. On this diagram, whereas the design variables are used to generate the initial population and their descendants in the second and third step, respectively, in the fourth step, the objective and constraints functions defined by (5)–(9) are evaluated.

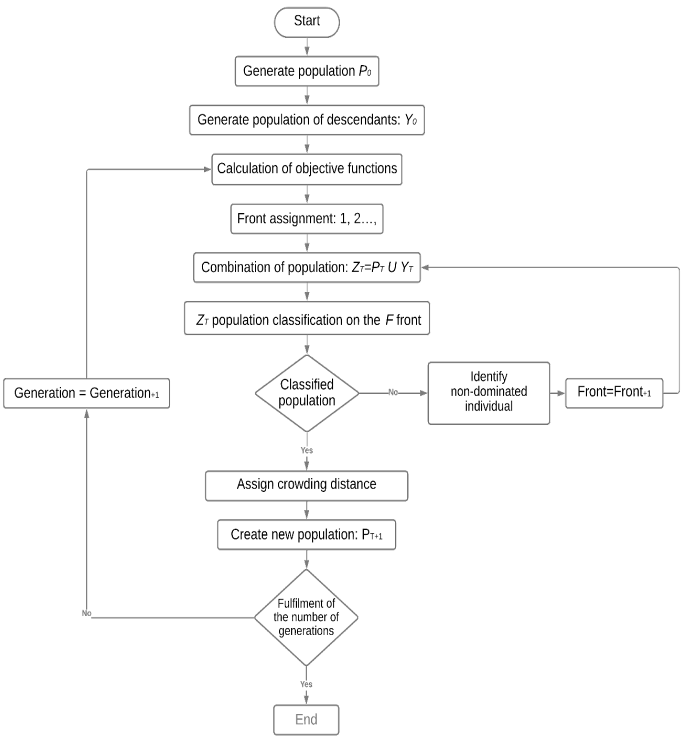

Figure 1. NSGA-II algorithm flowchart [19].

4. Numerical Results

Numerical results for optimizing an HFSW are presented. The tests were conducted by using a CPU with 1.6 GHz Intel core i5 and memory size 4 GB.

4.1. Found Solutions

The NSGA-II algorithm generates acceptable solutions based on population size (P), the number of generations (G), defined constraints and the search space defined by the design variables given in Table 1. Table 2 shows four solutions of the last generation for different values of P and G.

Table 2. Set of solutions found for different P and G values.

		Objectives		Design Variables						Constraints		
P	**G**	μ	V_F	**t**	**W**	**L**	h_a	h_m	s	(7)	(8)	(9)
200	200	0.986	497.249	16.371	57.690	85.842	0.121	1.983	0.205	0.036	2.751	87.228
		0.960	445.689	12.249	58.355	91.402	0.125	1.993	0.241	0.010	54.311	83.664
		0.952	365.519	11.551	57.281	89.345	0.125	1.972	0.209	0.002	134.481	82.499
		0.954	415.011	11.715	58.005	84.922	0.128	1.939	0.208	0.004	84.989	89.092
400	400	0.964	420.480	12.671	75.585	91.314	0.102	1.999	0.258	0.013	79.520	135.442
		0.983	484.063	15.568	70.908	86.127	0.101	1.998	0.249	0.033	15.937	126.599
		0.952	399.941	11.602	71.475	87.568	0.103	1.925	0.266	0.002	100.059	126.857
		0.958	401.298	12.125	73.624	89.531	0.101	2.000	0.265	0.008	98.702	131.339
600	600	0.970	448.090	13.357	30.290	78.446	0.100	2.000	0.574	0.020	51.911	12.423
		0.957	489.734	12.036	35.909	77.218	0.100	1.998	0.582	0.007	10.266	30.508
		0.968	401.445	13.122	27.446	74.869	0.100	2.000	0.556	0.018	98.555	7.468
		0.970	422.962	13.384	26.367	74.646	0.101	2.000	0.589	0.020	77.038	4.455

From the third column of Table 2, $\mu > 0.95$ (or as a percentage $\mu > 95\%$), ensuring not only a value of 20 mg/L of BOD_5 at the outlet of the HFSW but also complying with the NOM-003-SEMARNAT-1997 standard in Mexico. Further, V_F is less than 500 m^3 for all cases as shown in the fourth column, and all constraints are satisfied as can be seen in the last three columns of Table 2.

4.2. Pareto Front

The Pareto front is generated by post-processing all data generated by the evolutionary optimizer using Matlab Online [20], based on the confrontation of objectives with population and generation values at 200, 400 and 600, respectively. In this sense, given a vector of design variables, **x** is said to be dominated over by other vector of design variables **y** if

$$\mathbf{x} \textit{ dominates } \mathbf{y} \Leftrightarrow f_n(\mathbf{x}) < f_n(\mathbf{y}) \; \forall i \in \{1, \ldots, n\} \tag{11}$$

Otherwise, **x** is said to be a Pareto front if **x** is non-dominated by any other vector of design variables $\mathbf{z} \in \mathrm{X}$ such that $f(\mathbf{x}) < f(\mathbf{z})$ [14]. In this way, Figure 2a shows that with a lower number of population and generation, there is greater dispersion of the solutions. Increasing P and G, a higher population density is obtained and results in a better observation of the behavior of the non-dominated solutions and the Pareto front as illustrated in Figure 2b,c. Here, each blue point represents an acceptable design for HFSW that satisfies the constraints.

Figure 3 shows the ideal Pareto front vs. the found Pareto front, where P = G = 600 are used. Clearly, Figure 3 shows a min–max problem, and all individuals of the population are in the search space with the constraints above defined. Therefore, all solutions are valid. Additionally, any blue point in Figure 3 (right side) can be selected, and the numerical value of each design variable can automatically be obtained. But also, all the found solutions can be stored in a database in order to be used in a next process, saving CPU resources.

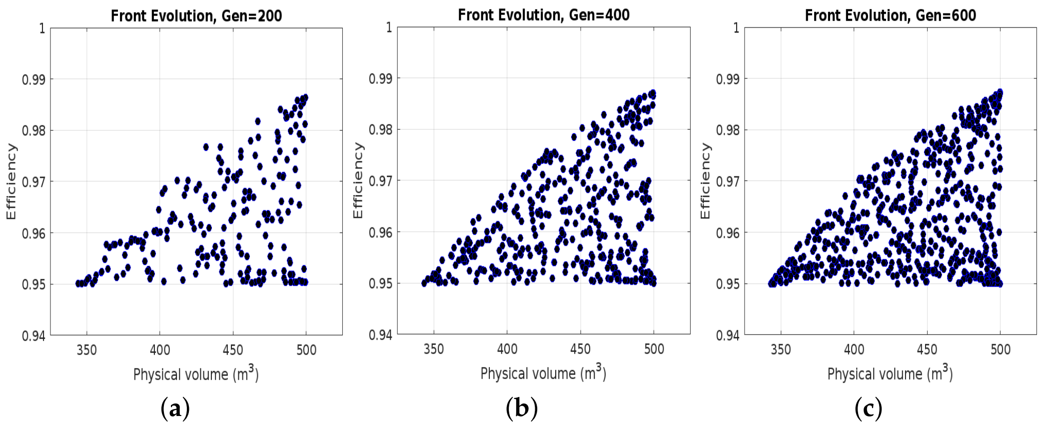

Figure 2. Dispersion in Pareto front: (**a**) P = 200, (**b**) P = 400 and (**c**) P = 600.

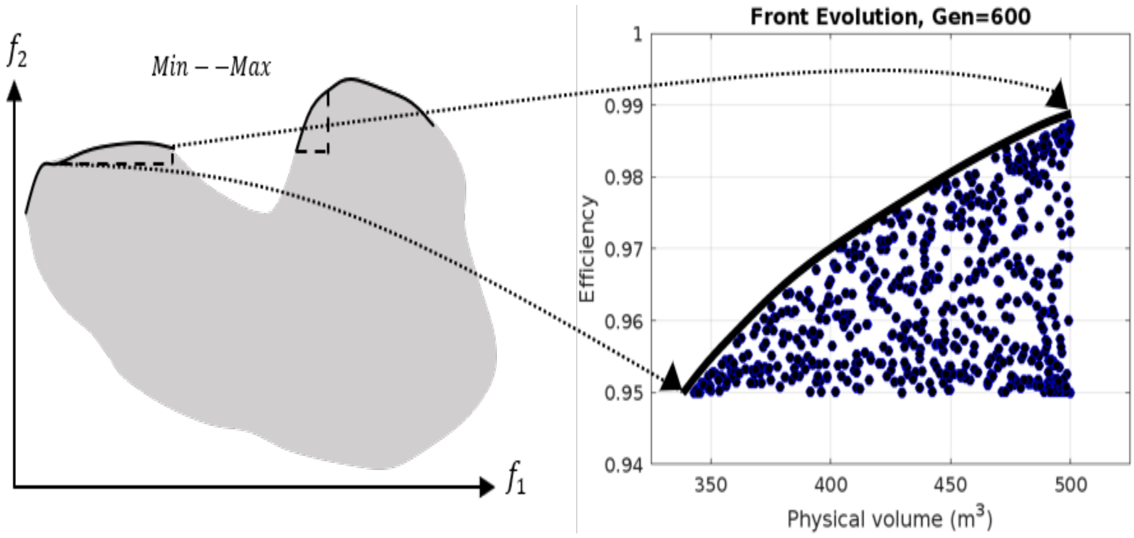

Figure 3. Ideal Pareto front (**left side**) vs. found Pareto front (**right side**).

In this sense, and selecting a solution point on the Pareto front of Figure 3 (right side), the design of the HFSW is represented in Figure 4. From this solution, we obtain $\mu = 0.968$ (equivalent to $\mu > 96.8\%$), $V_F = 401.445$ m^3, where the numerical values of each design variable for the construction of HFSW are $t = 13.122$ d, $W = 27.446$ m, $L = 74.869$ m, $h_a = 0.1$ m, $h_m = 2$ m and $s = 0.556\%$ as given in the penultimate row of Table 2. The results indicate that the NSGA-II algorithm, adapted to the specific characteristics of wetlands, manages to generate solutions that optimize the efficiency of wastewater treatment, which supports its viability and usefulness in wastewater management.

Moreover, we compare the results generated by the proposed methodology associated with an individual of the Pareto front with those designs of HFSW reported in the literature as described in Table 3. It is found that all works are fully custom designs and some of them have small dimensions, limiting the volume capacity in gray-water treatment. Further, all cited references not only do not report the numerical value of the design variable h_a used but also almost all them use a slope equal to 1, and μ is lower compared to the result obtained with the proposed methodology. Furthermore, it can also be observed that t tends to increase when V_F also increases and, therefore, results in greater volume capacity in gray-water treatment. It is important to mention that, whereas one fully custom design is reported in [4,5,10,12], with the developed methodology, P acceptable designs are generated. For instance, from Figure 2c, we have P = 600 acceptable artificial wetland designs. As a consequence, any physical design represented by a blue point of Figure 3 can be selected, and its design features are much better that those reported in Table 3.

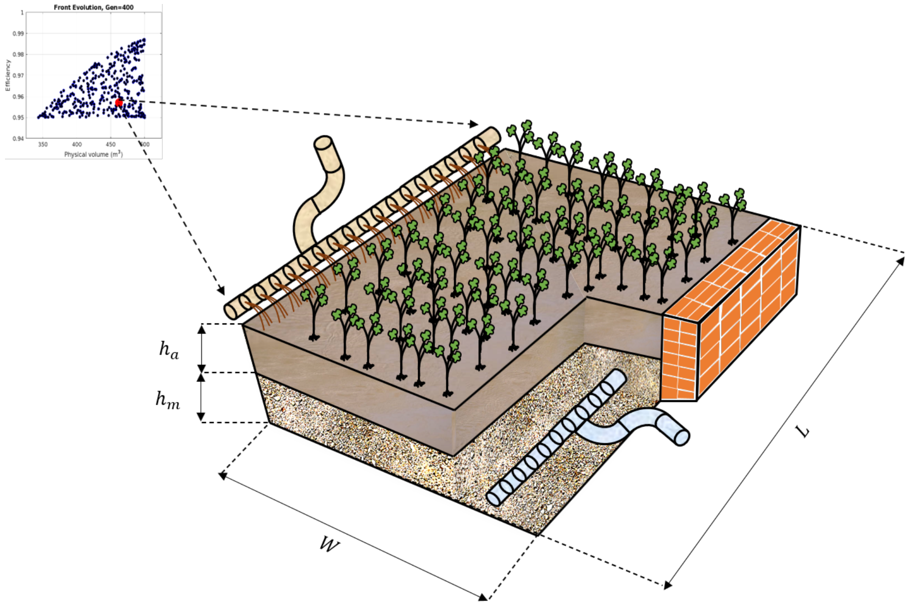

Figure 4. Scheme of the design of the HFSW.

Table 3. Comparison with other works.

	[4]	[5]	[10]	[12]	**This Work**	**Units**
V_F	279.68	0.432	3.136	6.000	401.445	m^3
μ	-	96.00	93.00	90.30	96.80	%
t	7.000	7.000	4.370	3.000	13.122	d
W	16.000	0.600	1.320	2.000	27.446	m
L	23.000	1.200	3.960	4.000	74.869	m
h_m	0.760	0.600	0.600	1.000	2.000	m
h_a	-	-	-	-	0.100	m
s	1.000	1.00	1.000	0.800	0.556	%

5. Discussion

The use of the NSGA-II algorithm allows us to explore a wide range of solutions and generate the Pareto front. This front not only represents the non-dominated solutions but also offers a clear view of the balance between objective functions. By considering different values of P and G during the optimization process, a better understanding of the behavior of the solutions is provided. Therefore, with high values of P and G, the Pareto front is better formed, providing a valuable tool for decision making since it allows different design options to be evaluated based on specific design variables and constraints. Regarding the established constraints, these can also be evident on the Pareto front since the multi-objective optimization algorithm has identified solutions that exceed the 95% contaminant removal threshold, maintaining the V_F at below 500 m^3. This finding demonstrates the effectiveness and ability of the NSGA-II algorithm to optimize the HFSW design. A disadvantage of the proposed HFSW design methodology is that if more objective functions are used along with constraints, the multi-objective optimization process becomes more complex and not only are more CPU resources required but the space of design must also be expanded in order to search for a better combination of all the design variables that satisfy all the objective and constraint functions. As a consequence, more CPU time is required since P and G also must be increased in order to obtain greater diversity. Furthermore, the evolutionary optimizer could also fail since it is limited to using a low number of objective functions. This is another disadvantage since the real design of an HFSW consists of several objective functions, both biological and physical, among others. In this sense, the proposed design methodology can also be used for optimizing the biological part of an HFSW and then merging both Pareto fronts, the one generated for the physical part and for the biological part. As a consequence, it is possible to obtain an acceptable final design of the HFSW. Moreover, because the NSGA-II algorithm is based on genetic algorithms and the crossover and mutation probability indices are usually kept constant throughout the optimization process, it is possible to generate identical individuals between generations. As a consequence, local optimal solutions are found. Note that this last behavior is also due to the fact that NSGA-II is elitist, and the best individuals found in each generation are always kept on the Pareto front. A possible solution to this problem is to randomly change the mutation and crossover probability indices between generations or perhaps combine other optimization algorithms with NSGA-II. These tasks are lines of future work.

6. Conclusions

This research demonstrates that using the NSGA-II algorithm for HFSW management is a promising strategy to address the specific changes associated with these types of ecosystems. It was possible to obtain the best solutions for the vector of design variables and represent the Pareto front and, therefore, at a smaller population size P and fewer generations G of greater dispersion, given that the solution of the design variables for HFSW with the input data P and G has greater dispersion. The solution of design variables, found by the NSGA-II algorithm, depends on the values of P and G, the constraint and objective functions. These results suggest that optimization with the NSGA-II algorithm can play a crucial role in the constructed wetland, providing tools for data-driven decision making and implementing sustainable management practices and strategy to the peculiarities of the HFSW. However, the evolutionary optimizer is limited to using few objective and constraint functions since increasing their number not only increases the complexity of the solution but also increases the use of CPU resources, and the optimizer cannot find acceptable solutions. This is a serious disadvantage since the real design of artificial HSFWs is composed of several physical and biological performance objectives that must be satisfied simultaneously, and this is a conflict that exists among them.

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