Anexos

Anexo A: Modelo matemático para la distribución del agua en la cuenca del río Machángara.

El modelo matemático fue planteado en (Veintimilla-Reyes et al., 2019) con mayor detalle en el capítulo 2. En este anexo se presentan las fórmulas y variables que fueron implementadas en Python para ser usadas por el paquete de Pymoo y resolver el problema con PSO. En la *Fig. A - 1* se puede observar la función objetivo para la distribución del agua en un sistema de río con reservorios.

$$\text{Minimize } \sum_n \sum_d \sum_t \left(\mathrm{P_d} * \mathrm{S}^{t-}_{n,d}\right) + \sum_n \sum_d \sum_t \left(\mathrm{E}_d * \mathrm{S}^{t+}_{n,d}\right) + \sum_r \sum_t (\mathrm{U_r} * \mathrm{SH}^{t-}_{r}) + \sum_r \sum_t (\mathrm{A_r} * \mathrm{OF}^{t+}_{r}) + \sum_n \sum_t (\mathrm{W_n} * \mathrm{T}^{t+}_{n,n+1}) + \sum_n \sum_t (\mathrm{B_n} * \mathrm{Q}^{t-}_{n,n+1}) + \sum_n \sum_d \sum_t (\mathrm{F}_d * \mathrm{MinXD}^{t-}_{n,d}) + \sum_n \sum_d \sum_t \left(\mathrm{G}_d * \mathrm{MaxXD}^{t+}_{n,d}\right)$$

Fig. A - 1. Función objetivo para la distribución del agua en un sistema de río con reservorio.

En la ecuación de la Fig. A - 1 se tiene:

- El primer término se refiere a las demandas insatisfechas ($S^{t-}_{n,d}$) y sus correspondientes penalizaciones (P_n);
- El segundo término ($S^{t+}_{n,d}$) está relacionado con las penalidades cuando se asigna más agua de la requerida a un nodo de demanda;
- Los términos (SH^{t-}_{r}) y (OF^{t+}_{r}) están relacionados con una penalización por no alcanzar el volumen mínimo en y por exceder la capacidad máxima de los embalses respectivamente
- El quinto término ($T^{t+}_{n,n+1}$) está relacionado con la sanción por crecida de un segmento de río;
- El sexto término ($Q^{t-}_{n,n+1}$) se refiere a la penalización asociada al caso de falta de agua en un segmento de río;
- Los términos ($MinXD^{t-}_{n,d}$) y ($MaxXD^{t+}_{n,d}$) están relacionados con la penalización de no alcanzar el volumen mínimo y exceder la capacidad de un segmento de demanda respectivamente.

Las restricciones consideradas dentro del problema son visibles desde la *Fig. A - 2*.

a) Mass balance constraints

1. Transport (n)

$$X^t_{n-1,n} + \sum_i X^t_{i,n} + \sum_r X^t_{r,n} + V^{t-1}_n + TD^{t-2}_{n-2,n-1} + TDFW^{t-2}_{n-2,n-1} + RW^t_{n-1,n} + OF^{t+}_r + \sum_d RD^{t-2}_{d-2,d-1} = V^t_n + LP^t_n + X^t_{n,n+1} + \sum_r X^t_{n,r} + \sum_d X^t_{n,d} + TD^t_{n,n+1} + L^t_{n-1,n} + L^t_{r,n} + L^t_{n,d} \qquad n \in N,\ n > 1,\ \forall_t \in T,\ \forall_i \in I$$

2. Reservoir (r)

$$\sum_n X^t_{n,r} + \sum_i X^t_{i,r} + V^{t-1}_r = \sum_n X^t_{r,n} + V^t_r + \sum_n X^t_{r,d} \qquad \forall_r \in R,\ \forall_n \in N$$

Fig. A - 2. Restricciones del balance de agua.

b) Network limitations and capacity constraints

1. Network limitations

Inputs (i)

$$\sum_i X^t_{i,n} = X^t_{n,n+1} \qquad n \in N,\ n > 1,\ \forall_i \in I$$

Sources (i)

$$\sum_n X^t_{i,n} = I^t_i \qquad n \in N,\ \forall_i \in I$$

Demands (d)

$$\sum_n X^t_{n,d} + S^{t-}_d - S^{t+}_d = D^t_d \qquad n \in N,\ n > 1,\ \forall_d \in D$$

2. Capacity constraints

River Segment (n)

$$X^t_{n,n+1} + T^{t-}_{n,n+1} - T^{t+}_{n,n+1} = Cmax^t_{n,n+1} \qquad n \in N,\ n > 1,\ \forall_t \in T$$

$$X^t_{n,n+1} + Q^{t-}_{n,n+1} - Q^{t+}_{n,n+1} = Cmin^t_{n,n+1} \qquad n \in N,\ n > 1$$

Reservoir (r)

$$V^t_r - LP^t_r - OF^{t+}_r + OF^{t-}_r = Rmax^t_r \qquad \forall_r \in R$$

$$V^t_r - LP^t_r + SH^{t-}_r - SH^{t+}_r = Rmin^t_r \qquad \forall_r \in R$$

Demand segment (d)

$$X^t_{n,d} + MinXD^{t-}_{n,d} - MinXD^{t+}_{n,d} = Cmin^t_{n,d} \qquad n \in N,\ n > 1,\ \forall_d \in D$$

$$X^t_{n,d} + MaxXD^{t-}_{n,d} - MaxXD^{t+}_{n,d} = Cmax^t_{n,d} \qquad n \in N,\ n > 1,\ \forall_d \in D$$

Fig. A - 3. Restricciones para los límites de la red que representa el río.

c) Continuity constraints

$$V_n^t \leq \beta_n^t * \left(\sum_i X_{i,n}^{t-1} + \sum_r X_{r,n}^{t-1} + V_n^{t-1} + X_{n-1,n}^t + RW_{n-1,n}^t + +TDFW_{n-2,n-1}^{t-2}\right) \qquad n \in N,\; n > 1,\; \forall_i \in I,\; \forall_r \in R$$

$$V_n^t \geq \gamma_n^t * \left(\sum_i X_{i,n}^{t-1} + \sum_r X_{r,n}^{t-1} + V_n^{t-1} + X_{n-1,n}^t + RW_{n-1,n}^t + +TDFW_{n-2,n-1}^{t-2}\right) \qquad n \in N,\; n > 1,\; \forall_i \in I,\; \forall_r \in R$$

Fig. A - 4. Restricciones de continuidad o flujo del agua.

d) Time delay constraints

Transfer nodes

$$TD_n^t = \delta_n^t * \left(X_{n,n+1}^t\right) \qquad n \in N,\; n > 1$$

Flooded Water (n)

$$TDFW_{n,n+1}^t = \mu_n^t * \left(T_{n,n+1}^{t+}\right) \qquad \forall_n \in N,\; n > 1$$

Fig. A - 5. Restricciones de retraso del agua en cada salto de tiempo.

e) Losses

In river segment (n)

$$L_{n-1,n}^t = \propto_{n-1,n}^t * \left(X_{n-1,n}^t\right) \qquad n \in N,\; n > 1$$

In segment between reservoir and transfer node (r)

$$L_{r,n}^t = \propto_{r,n}^t * \left(X_{r,n}^t\right) \qquad n \in N,\; n > 1,\; \forall_r \in R$$

In segment between transfer and demand node (d)

$$L_{n,d}^t = \propto_{n,d}^t * \left(X_{n,d}^t\right) \qquad n \in N,\; n > 1,\; \forall_d \in D$$

In Reservoir (r)

$$LP_r^t = \theta_r^t * \left(V_r^t\right) \qquad \forall_r \in R$$

Of flooded water (n)

$$LFW_{n,n+1}^t = \Delta_{n,n+1}^t * \left(T_{n,n+1}^{t+}\right) \qquad n \in N,\; n > 1$$

Fig. A - 6. Restricciones para simular la pérdida de agua en el sistema de río.

f) Floods

Flood water returning to river segment (n)

$$RW_{n,n+1}^t = T_{n,n+1}^{t+} - LFW_{n,n+1}^t - TDFW_{n,n+1}^t \qquad n \in N,\; n > 1$$

Water returning from a demand node to a reservoir node

$$RD_{r,d}^t = \left(1 - \propto_{r,d}^t\right) * \left(X_{r,d}^t\right) \qquad \forall_d \in D,\; \forall_r \in R$$

Fig. A - 7. Restricciones para la simulación de inundaciones.

Las variables y su significado se detallan a continuación:

Type	Notation	Description	Unit
Indices	i	input node ∈ I	-
	r	reservoir node ∈ R	-
	d	demand node ∈ D	-
	n	transfer node ∈ N	-
	t	time step ∈ T	-
Parameters	P_d	Penalty for not meeting the demand with one unit	Monetary units (mu)/volume (uv)
	E_d	Penalty for exceeding the demand with one unit	mu/uv
	F_d	Penalty for not meeting the minimum capacity in a demand segment with one unit	mu/uv
	G_d	Penalty for exceeding the maximum capacity in a demand segment with one unit	mu/uv
	W_n	Penalty for having a one unit flood in segment (n, n+1)	mu/uv
	B_n	Penalty for not meeting the minimum capacity in segment (n, n+1) with one unit	mu/uv
	U_n	Penalty for not meeting the minimum capacity of a reservoir with one unit	mu/uv
	A_n	Penalty for exceeding the maximum capacity of a reservoir with one unit	mu/uv
	$\propto^t_{n,n+1}$	Loss factor associated with the river segment (n, n+1) at time step (t), to be calibrated	-
	$\propto^t_{r,d}$	Loss factor associated with the reservoir node and a demand node (r, d) at time step (t), to be calibrated	-
	$\propto^t_{n,d}$	Loss factor associated with the transfer node and a demand node (n, d) at time step (t), to be calibrated	-
	θ^t_r:	Loss factor associated to a reservoir at time step (t), to be calibrated	-
	$\mu^t_{n,n+1}$	Time delay factor associated with the water excess in a river segment (n, n+1) at time step (t), to be calibrated	-
	$\Delta^t_{n,n+1}$:	Loss factor associated with the water excess in a river segment (n, n+1) at time step (t), to be calibrated	-
	β^t_n:	Percentage of water that must flow from the nth node to the next one at step time (t), to be calibrated	-
	$\gamma^t_{n,}$:	Percentage of water that must remain in the nth node until the next time step (t), to be calibrated	-
	$\delta^t_{n,n+1}$:	Percentage of water that flows to the next node with a time delay in time step (t), to be calibrated	-
	$Cmin^t_{n,n+1}$	Minimum capacity of the river segment (n, n+1) at time step (t)	uv

	$Cmax_{n,n+1}^{t}$	Maximum capacity of the river segment (n, n+1) at time step step (t).	uv
	$Cmin_{n,d}^{t}$	Minimum capacity of a demand segment (n,d) at time step (t)	uv
	$Cmax_{n,d}^{t}$	Maximum capacity of a demand segment (n,d) at time step (t)	uv
	I_{i}^{t}	Amount of water arriving at the input node (i) at time step (t)	uv
	$Rmax_{r}^{t}$	Maximum capacity of a reservoir at time step (t)	uv
	$Rmin_{r}^{t}$	Minimum capacity of a reservoir at time step (t)	uv
Variables	V_{n}^{t}	Amount of water in a node (n) at time step (t)	uv
	D_{d}^{t}	Amount of water needed to meet demand (d) at time step (t)	uv
	V_{r}^{t}	Amount of water in the reservoir (r) at time step (t)	uv
	$X_{n,n+1}^{t}$	Flow between the nodes (n) and (n+1) at time step (t).	uv / time step
	$X_{r,n}^{t}$	Flow between a reservoir node (r) and a transfer node (n) at time step (t)	uv / time step
	$X_{n,r}^{t}$	Flow between a transfer node (n) and a reservoir node (r) at time step (t)	uv / time step
	$X_{i,n}^{t}$	Flow between an input node (i) and a transfer node (n) at time step (t)	uv / time step
	$X_{i,r}^{t}$	Flow between an input node (i) and a reservoir node (r) at time step (t).	uv / time step
	$X_{n,d}^{t}$	Flow between a transfer node (n) and a demand node (d) at time step (t)	uv / time step
	$X_{r,d}^{t}$	Flow between a reservoir node (r) and a demand node (d) at time step (t)	uv / time step
	TD_{n}^{t}	Delayed flow from upstream nodes and coming into node (n) at time step (t)	uv / time step
	$L_{n,n+1}^{t}$	Amount of water lost during the flow from transfer node (n) to transfer node (n+1) in time step t	uv
	$L_{r,n}^{t}$	Amount of water lost during the flow from reservoir node (r) to a transfer node (n) in time step t	uv
	$L_{n,d}^{t}$	Amount of water lost during the flow from transfer node (n) to demand node (d) in time step t	uv
	LP_{r}^{t}	Amount of water lost in a reservoir node (r) during time step t	uv
	$LFW_{n,n+1}^{t}$	Amount of water lost from the water flooded while flowing from node (n) to node (n+1) in time step t	uv
	$RW_{n,n+1}^{t}$	Amount of flooded water flowing back to a node (n+1) from node (n) during time step t	uv
	$RD_{r,d}^{t}$	Amount of water flowing back to a reservoir node (r) from a demand node (d) in time step t	uv
	$TDFW_{n,n+1}^{t}$	Amount of water flowing from node (n) to node (n+1) with a delay due to flooding in time step t	uv
Slack Variables	$S_{n,d}^{t-}$	Amount of water that cannot be allocated to demand (d) at time step (t)	uv
	$S_{n,d}^{t+}$	Amount of water that exceeds the demand (d) at time step (t)	uv
	$T_{n,n+1}^{t+}$	Amount of water above the maximum capacity of segment (n, n+1) at time step (t)	uv
	$T_{n,n+1}^{t-}$	Amount of water under the maximum capacity of segment (n, n+1) at time step (t)	uv
	$Q_{n,n+1}^{t-}$	Amount of water under the minimum capacity of segment (n, n+1) at time (t)	uv
	$Q_{n,n+1}^{t+}$	Amount of water above the minimum capacity of segment (n, n+1) at time step (t)	uv
	OF_{r}^{t+}	Amount of water above the maximum capacity of reservoir (r) at time step (t)	uv
	OF_{r}^{t-}	Amount of water under the maximum capacity of reservoir (r) at time step (t)	uv
	SH_{r}^{t-}	Amount of water under the minimum capacity of reservoir (r) at time step (t)	uv
	SH_{r}^{t+}	Amount of water above the minimum capacity of reservoir (r) at time step (t)	uv
	$MinXD_{n,d}^{t-}$	Amount of water under the minimum capacity of demand segment (n, d) at time step (t)	uv

$MinXD_{n,d}^{t+}$	Amount of water above the minimum capacity of demand segment (n, d) at time step (t)	uv
$MaxXD_{n,d}^{t-}$	Amount of water under the maximum capacity of demand segment (n, d) at time step (t)	uv
$MaxXD_{n,d}^{t+}$	Amount of water above the maximum capacity of demand segment (n, d) at time step (t)	uv

Anexo B: Artículo científico publicado de la revisión de literatura.

Se publicó un artículo dentro de esta tesis titulado "Optimization Models Used in Water Allocation Problems in River Basin with Reservoirs: A Systematic Review", que fue presentado en TICEC 2022 y está disponible en el libro DSICT 2022 (Guerrero et al., 2022).

Optimization Models Used in Water Allocation Problems in River Basin with Reservoirs: A Systematic Review

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Abstract. In recent years, several works dedicated to obtaining optimization models have been published. Many of them have been applied in the management of water resources, especially since water is a vital resource that brings economic, social and environmental benefits. The main objective of this article is to review the published literature on optimization models and understand what methods their authors used to solve optimization problems in water allocation in a river basin with reservoirs. A systematic methodology was applied to select research questions, digital databases and search terms to later use practical and methodological filters to carry out this systematic review. This procedure allowed a review and synthesis of the results obtained on the optimization models. It was found that the models resulting from the systematic review vary depending on the objectives set by the diverse authors. However, algorithms based on particle swarm optimization (PSO) have a greater presence compared to the rest of the algorithms present in this systematic review.

Keywords: Systematic review · Water allocation · River basin · Meta-heuristics · Heuristics · Reservoirs

Introduction

Water is an important resource that can be represented by a nexus known as the WEF-nexus (water-energy-food nexus). The nexus includes water supply, sewage treatment, and hydro-power generation in a reservoir water system [1]. The optimal design of a water allocation system that meets this nexus has become an urgent research topic [2].

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The allocation of water in a river basin with reservoirs can be optimized to meet the demands of different nodes that seek to comply with the WEF-nexus. This optimization problem can be approached with different methods, one of them being heuristic and meta-heuristic methods [3]. These methods have been applied in other problems related to the management of water resources; including, optimization of reservoir operation, distribution of water through pipelines, expansion of the capacity of water infrastructure facilities, water conduction problems/shortest water route, etc. [4]. It should be noted that in all these studies the objectives to be optimized were exclusive to the study area. The objectives vary as the methods applied. For this reason, it is intended to carry out a systematic literature review on heuristic or meta-heuristic methods applied specifically in water allocation optimization problems in a river system with reservoirs.

As indicated above, systematic reviews focusing on water resources and heuristic methods are found in the literature, but an exclusive systematic review for optimizing water allocation in a river system with reservoirs is not found. The rest of the paper is organized as follows. Section 2 indicates the methodology used to review the optimization models systematically. Section 3 presents the results and discussion. Finally, the conclusion of the document is provided in Sect. 4.

Materials and Methods

The systematic review design responded to the purpose of collecting, selecting, evaluating and summarizing the evidence found regarding the heuristic or meta-heuristic methods that have been applied in optimization problems of water allocation in a river system with reservoirs. To carry out this systematic review, the Fink methodology was used, which consists of the following tasks: 1) Select Research Questions, 2) Select Bibliographic Databases and Websites, 3) Choose Search Terms, 4) Apply Practical Screen, 5) Apply Methodological Quality Screen, 6) Do the review and 7) Synthesize the results [5].

The systematic review began with the selection of the research questions. It was established that the main question to be answered was: What heuristic or meta-heuristic methods have been applied in water distribution optimization problems in a river system with reservoirs? Subsequently, the search sub-questions were defined, whose objective was to obtain information to delimit the field of research studied. These questions were: 1) What were the objectives of the water allocation optimization problems in the river basin? 2) What tools or solvers are used to solve optimization models? 3) What parts are involved in the optimization process? And 4) What indicators are used to analyze or validate the results of the optimization model?

Once the field of the research was defined, it was necessary to select the bibliographic databases and the websites. Google Scholar is selected because this search engine allows to incorporate personalized search strings with ‘and’ and ‘or’ operators; and also allows access to articles published in various journals and databases. To search for the primary articles to reference this work, a search string was defined, which is detailed in Table 1. The string was made up of the relevant terms and logical connectors, which made it possible to combine different terms and establish logical relationships between them. Articles referenced within the articles resulting from the search are also considered if they meet the criteria indicated in Table 1.

With the structured search string, 178 articles were retrieved. With the results obtained after applying the first filters, the articles that met the inclusion criteria were selected after reviewing titles, abstracts and keywords. Once all the filters were applied, a manual review of the articles was carried out to determine the secondary sources. A total of 43 articles were read to determine their reliability. Next, the articles were selected based on the use of an optimization method and the explanation on how to use

Table 1. Search criteria for the systematic literature review

Search string	(“heuristic” or “meta heuristic”) and (“optimization” and modeling or simulation) and (“water allocation”) and (river “basin” or “river” or river with “reservoirs”)
Search dates	2010–2022
Language	English and Spanish
Inclusion criteria	**Exclusion criteria**

Studies that apply heuristic or meta-heuristic methods for optimizing or simulating the allocation of water over a river basin or similar water systems. May or may not contain reservoirs	Studies focused exclusively on reservoir management, since the objective is the entire river system and not just the reservoir
Literature reviews that include heuristic or meta-heuristic methods applied in problems of optimization and/or simulation in a river system or similar	Distribution of water in cropping areas that do not consider the river system as part of the problem
Articles that include heuristics or meta-heuristics in hydro-logical projects that are similar to the allocation of water in a river system	Piped water distribution and groundwater allocation

it, the objective functions, the restrictions and the results obtained with their proposed model. In addition, the articles also had to meet the inclusion criteria detailed in Table 1. Through this selection, a total of 16 articles were obtained for the systematic review. It is worth mentioning that literature review articles related to this topic were also found, which provide an overview of heuristic methods, of which 6 literature reviews stand out.

Results and Discussion

This section presents the main findings on this systematic review and summarizes the results obtained after filtering the articles. Considering the inclusion criteria mentioned in the previous section, articles useful for this literature review were classified and can be seen in Table 1.

Research Questions

In the main research question of this literature review, which is: What heuristic or metaheuristic methods have been applied in water allocation optimization problems in a river system with reservoirs? To answer this question, the classification of heuristic algorithms mentioned in [6] should be mentioned, which can be seen in Fig. 1.

The classification showed in Fig. 1 plus the histogram (see Fig. 2) allow to observe that there is an emphasis on population-based algorithms, where algorithms of the

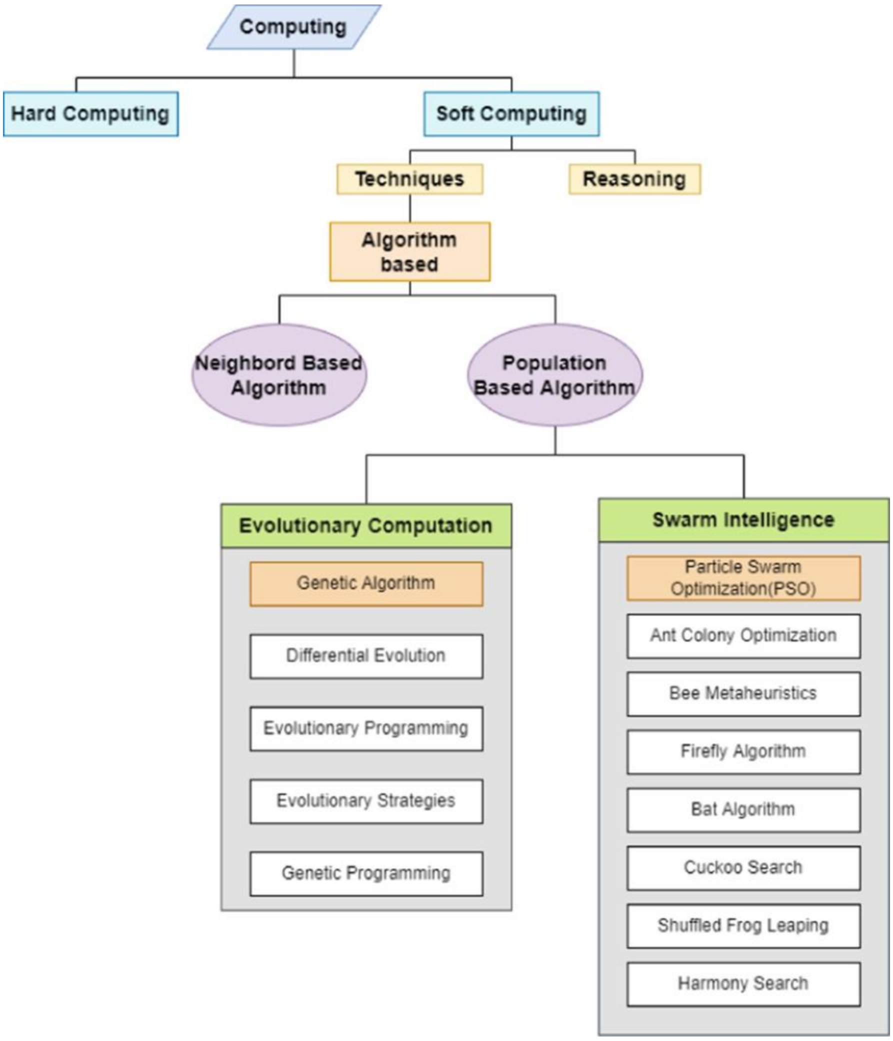

Fig. 1. Part of the classification of the heuristic algorithms by Kumar and Yavar [6].

"swarm intelligence" type have a greater presence with a total of 13 items. Within these articles, specific algorithms such as PSO, ACO, HS, etc., are applied.

In the research sub-question 1: What were the objectives of the water allocation optimization problems in the river basin? The articles reviewed had different objectives, however, the difference is that certain articles had the objective of testing or validating a novel hybrid algorithm, while other studies had the objective of solving the optimization problem without giving priority to the algorithm. Another of the objectives found is the focus on the reservoirs, but it should be emphasized that the study did not focus only on the reservoirs, however, it does present greater interest in these rather than the rest of the variables to be considered within the problem.

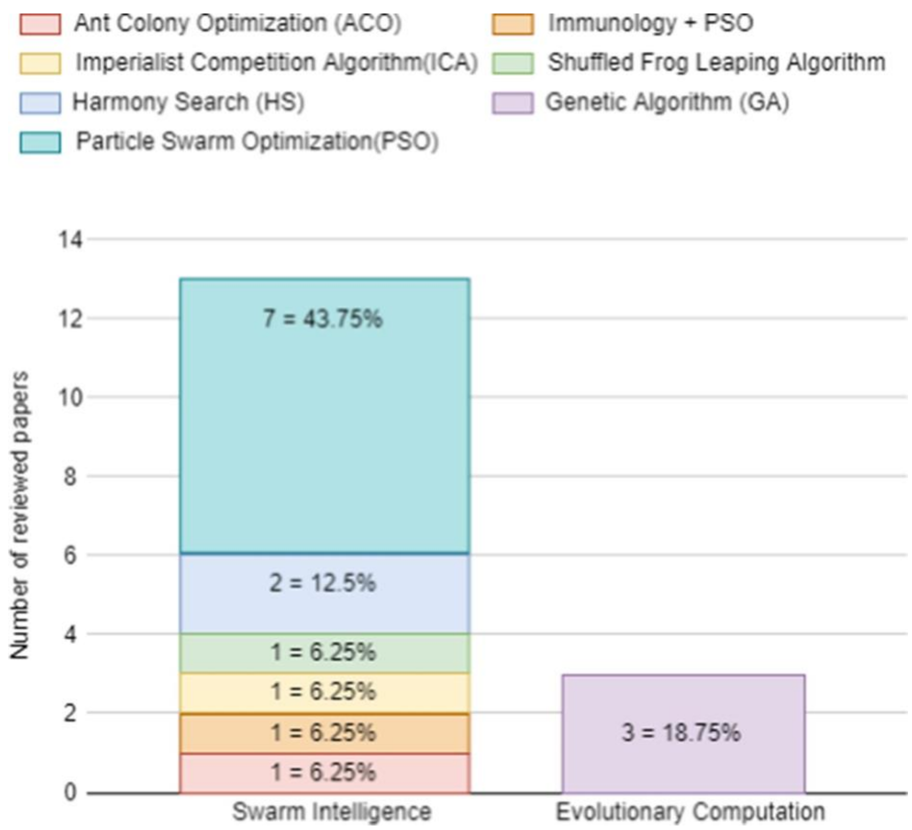

Fig. 2. Histogram of the heuristic methods used in the reviewed articles.

For example, [7] aims to find optimal values for a large number of water discharges in the network links (rivers and canals) and nodes (reservoirs and demands) while also looking for the optimal values of reservoir capacities and their storage priorities.

Another objective to highlight is the emphasis on social aspects. This is the case of [8], which proposes a socioeconomic model with two objectives. The first one is to maximize economic profitability and maximize employment. In the second objective the influence of water distribution on social welfare is considered. Other studies [2, 8– 11] also have a social approach when considering the allocation of water to meet the population's demand for water without considering whether there is economic benefit or not.

It is also considered an important objective to seek an ecological balance when allocating water. This is the case in studies [9, 11–14]. For example, in [14] the objective is summarized in minimizing water scarcity and the amount of contaminated water, but it also seeks to maximize economic interests including the generation of hydroelectric power. The other articles also presented several objectives, but they considered ecological balance important.

Several articles also mention the importance of agricultural areas [2, 8, 9, 12, 15–17]. For example, in [17] there is a focus on water allocation for irrigation that is compatible with climate change conditions in the Borkhar Plain in Iran.

In research sub-question 2: What tools or solvers are used to solve optimization models? Some of the articles decided to incorporate the heuristic methods with simulation models such as WEAP (water assessment and planning software) [12, 16] or MODSIM (software based on network flow programming) [17, 18]. The execution of heuristic algorithms can be done with MATLAB [2] or by programming with languages such as python. The articles do not specify in detail what software tools were used for the programming and/or execution of the algorithms, they only present the results.

In research sub-question 3: What parts are involved in the optimization process? The steps carried out in [8] encompasses the steps to follow in a study starting with data collection. In addition, it considers the distribution of water in the agricultural, industrial and human consumption area, with the incorporation of social and economic criteria. The parts involved are summarized in: Data collection, preparation of the optimization model and implementation of the model. In the data collection is contemplated the water sources, necessary statistics (economic, population, etc.) and existing data on water resources. When preparing the optimization model, the decision variables, objectives and restrictions must be defined. For the implementation part, the execution of the optimization model is included as well as the analysis of the results based on what is indicated in the objectives of the study.

In the research sub-question 4: What indicators are used to analyze or validate the results of the optimization model? Two general forms of validation of results can be observed. The first way is to compare the developed meta-heuristic model with another heuristic model [2,11,19,20]. The second way is to analyze the Pareto front and consider the different trade-offs between the objectives [2, 9, 10, 12, 14, 16]. Comparisons are also made with the current situation, as is the case of [8], where the PSO algorithm gave results that produced a growth of 38% in economic benefits and profitability in the agricultural sector, a growth of 86% in the industrial sector and overall economic growth of 54% relative to current condition.

The results of the systematic review have revealed the main characteristics of two families of recurrent optimization methods, such as algorithms based on evolution and algorithms based on population intelligence. Furthermore, it is highlighted that these methods could work alone or be combined with other optimization processes, simulation techniques or meta-models to improve model performance.

In addition to minimizing water scarcity in demand areas for human consumption, there is also interest in distributing water in industrial and agricultural areas. These areas not only produce goods such as food but can also be a job generator and produce economic benefit to the region. Another interest is how the allocation of water can affect the environment and also how to comply with the ecological well-being of the region. The area that appears most in the revised bibliography is the socioeconomic part. This area is large and encompasses social aspects such as the right to access to drinking water as well as the reduction of costs (costs in reservoirs, agricultural production that will give more income, industrial production that brings economic income and also a source of job, etc.). These areas can present conflicts. For example, to increase the economic benefit in an area such as the industrial one, the amount of water in the agricultural area can be restricted.

The articles found for this literature review have simulation-optimization approaches, multi-objective optimization, improvements of classical algorithms, or construction of hybrid algorithms. In this study context, simulation-optimization models refer to the process of incorporating a meta-heuristic algorithm into a simulation model. For example, in [16] this approach is used. WEAP is the simulation model, which consists of a water evaluation and planning software that optimizes water distribution decisions using linear programs [12]. But water distribution optimization problems are usually nonlinear on a large scale, so it is possible to integrate this WEAP system with the meta-heuristic algorithm to optimize the problem. In this way, the general framework consists of defining the objective functions, executing the meta-heuristic algorithm and determining if the objective was met using the simulation (WEAP) to evaluate the objective functions with the values found by the meta-heuristic algorithm.

Another term to mention is multi-objective optimization. In order to understand the concept, is necessary to emphasize that there are different approaches for handling constraints in evolutionary algorithms [21], which include: penalty functions, repair operators or local search, modified matching/mutation operators that preserve constraints, and multi-objective formulations where constraints are reformulated as objectives. Multiobjective optimization seeks to approximate Pareto optimal trade-offs between conflicting objectives. These trade-offs are made up of the set of solutions that are better than all other solutions in at least one objective and are called non-dominated or Pareto optimal solutions [22]. A strength of multi-objective optimization is its ability to quickly approximate the true Pareto surface, even if it is not exactly quantified [21].

Starting with the classical PSO algorithm, which is based on the social behavior of flocks of birds to search through multidimensional dimension spaces, it has been widely used in the optimization of water resource systems [16] and it is also one of the most recurrent algorithms within this systematic review (table). This algorithm has been applied in conjunction with the multi-objective and simulation-optimization approach. In [16] both approaches are used generating a MOPSO-WEAP model to analyze the effectiveness of a water distribution project. In this case WEAP is the simulation model while MOPSO is the heuristic goal. Two objective functions were defined which were to minimize the sizes of the project infrastructures and to maximize the reliability of the water supply to the agricultural lands. The results of applying optimization-simulation with PSO (MOPSO-WEAP) indicated that the project can meet these objectives.

Another study that uses the simulation-optimization technique is the one carried out in [17], which in this case uses MODSIM (based on network flow programming) as a simulation model and it is combined with the optimization algorithm Gray Wolf (GWO – Gray Wolf Optimization) to obtain the optimal amounts of irrigation and crop areas in the plain under two conditions: status quo, and with flows affected by climate change. The studied basin is the Zayandehroud basin, first its network is elaborated in the MODSIM model and the information related to each node is entered based on the data measured in the meteorological and hydrometric stations. The objective function of the model is to maximize profits from crop production and plan the optimal distribution of water.

Continuing with the line of studies where simulation and optimization are applied, is the one carried out in [18]. This study affirms that the simulation system would avoid having variables, functions, relationships, among others, and also achieve a continuous system. But the meta heuristic must evaluate the objective function on this simulation, which becomes computationally intensive. For this they propose the meta-model, which is used to produce computationally efficient substitutes for high-fidelity models. The most common are ANN, SVM, kriging and polynomial functions, which are evaluated in a water allocation problem based on surrogate optimization in the Atrak river basin in Iran. The simulation model used is MODSIM, which is a tool that allows analyzing the operation of river systems as networks of nodes and segments. While the applied heuristic goal is PSO. As conclusions, they determine that the ANN and SVM metamodels work better than others by saving the cost of evaluating the objective functions on the original model.

Another approach used is algorithm improvement. The study carried out by [23] uses a metaheuristic algorithm based on PSO, the Whale Optimization Algorithm (WOA). And on this algorithm, it uses an improvement (AWOA) to obtain a higher rate of convergence and precision. The aim of this study is to test the improvement versus traditional WOA and PSO algorithms for multi-objective water resource allocation resolution. In this case, the AWOA results indicate that there is higher convergence accuracy.

Hybrid algorithms are also presented, as is the case of [19], which integrates the weed optimization algorithm (WOA) and the particle swarm optimization algorithm (PSO), calling this hybrid WOAPSO. This algorithm is validated on two case studies, the first case study consists of an example of a river basin with 10 reservoirs, while the second is a hydropower optimization problem of three reservoirs in the Karoon river basin in Iran, which maximizes the efficiency index of hydroelectric power production. The results are compared with those obtained by the traditional algorithms of linear programming (LP), non-linear programming (NLP), WOA (in this case it is the weed algorithm - Weed Optimization Algorithm) and PSO; where WOAPSO proved to be more reliable in solving complex multi-reservoir systems in the context of integrated river basin management than classical optimization algorithms.

The next algorithm with the greatest presence is the genetic algorithm and its extensions. In [12] a Multi-Objective Optimization Genetic Algorithm (MOGA) is linked to Water Assessment and Planning (WEAP) software to optimize water allocation decisions over multiple years. The study region is Sistán, which is characterized as an arid zone, where the design variables of the problem consist of the cultivated area, the cultivation pattern and the wetland influx requirements for 30 years. The objective is to maximize the long-term net economic benefit and maximize the flow of water to the wetland. These objectives are incompatible between them, but the approach adopted in this study allows to obtain results that are analyzed by comparing purely economic scenarios versus multi-objective scenarios in the Pareto front. The authors also provide a description of the trade-offs in these scenarios to aid in the decision process for water resource stakeholders.

There is also the use of ant colonies (ACO) as an inspiration algorithm, which is a discrete combinatorial optimization algorithm based on the collective behavior of ants in their search for food. The literature review by [24] mentions that there are different versions of ACO that have proven to be flexible and powerful in solving a series of spatially and temporally complex water resource problems in discrete and continuous domains with unique objectives and/or multiple. One of the articles to highlight within this review is [13], which presents a multi-objective optimization framework with ACO to develop optimal trade-offs between water allocation and ecological benefit over a stretch of the Murray River in the South Australia. The results indicate that limited additional ecological benefit can be obtained as the allocation increases, by relaxing the flow constraints of the system. Additionally, the use of regulators can increase ecological benefits by using less water.

As indicated in the answer to question 4 of this systematic review, the majority of the authors of the reviewed articles include an analysis of the results. The analysis can be a comparison between optimization methods, or Pareto front analysis. It is also considered whether the algorithms can converge to an answer and the time taken. Another recurring analysis is the benefit obtained by optimizing the allocation of water and how much water was allocated to each demand node. Although not all the articles found are mentioned in detail, it can be seen that there is a strong inclination towards multiobjective methods and simulation-optimization. The improvement of classic algorithms or a mixture of algorithms to obtain new heuristics is also highlighted. Water resource management optimization problems in general are complex problems to be solved that depend on the number of variables to be considered, the objectives, the restrictions and the desired approach. Therefore, using improved metaheuristic, multi-objective and simulation-optimization methods turns out to be the best option for these problems. Another aspect to consider is the strong presence of PSO-based algorithms, since it offers a number of variants, as well as the flexibility to incorporate it with decision systems such as WEAP.

Conclusions

Although not all the articles found are mentioned in detail, it can be seen that there is a strong inclination towards multi-objective methods and simulation-optimization. The improvement of classic algorithms or the use of hybrid algorithms is also highlighted. Water resource management optimization problems in general are complex problems to be solved that depend on the number of variables to be considered, the objectives, the restrictions and the desired approach. Therefore, using improved meta-heuristic, multiobjective and simulation-optimization methods turns out to be the best option for these problems. In order to answer the main research question about which heuristic or metaheuristic methods have been applied in water allocation optimization problems in a river system with reservoirs, it has been found that each author decided to use the method that best adapted to their needs. However, it is necessary to mention that there is a strong presence of PSO-based algorithms, since it offers a number of variants, as well as the flexibility to incorporate it with decision systems such as WEAP.

Both PSO and the others algorithms mentioned in this review have their limitations. In the study carried out in [6], the advantages and disadvantages of some meta-heuristic algorithms in water resources problems, including PSO, are summarized. For PSO's family of algorithms, [6] mentions that the advantage of this type of algorithm is that they are simple to code and provide fast convergence, also implying a low computational cost. As a disadvantage, it is necessary to adjust parameters such as inertial weight, social and cognitive parameters. However, if the parameters are set correctly, the algorithm can achieve a global solution.

This systematic review aims to facilitate decision making on optimization models that can be used in water allocation optimization problems in a river system with reservoirs, considering the effectiveness and efficiency that these had when applied in real scenarios.

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Anexo C: Implementación en Pymoo para PSO.

Para la implementación en Pymoo se construye matrices de N x D, donde N es el número de iteraciones y D, el número de variables o dimensión del problema. En cada fase de calibración, validación e implementación esta dimensión va a variar ya que las variables se distinguen por que representan dentro del problema y también por el salto de tiempo en el que están. Si una variable representa la cantidad de agua en el reservorio, hay 60 variables distintas que representan la cantidad de agua en el reservorio de cada día dentro de dos meses. Para poder implementar las funciones objetivo y las restricciones se genera primero archivos que mantienen el tracking de las posiciones de las variables en cada salto de tiempo y construir las restricciones y calcular la función objetivo.

Una vez guardada la información de las posiciones se construye una clase hija de "ElementwiseProblem", que es una clase propia de Pymoo que permite agregar restricciones de igualdad, desigualdad y la función objetivo. También permite utilizar hilos de ejecución de Python y enviar funciones del tipo Repair para intentar disminuir el número de restricciones violadas por los valores originales encontrados por PSO y mover las partículas a una zona donde cumplan con más restricciones.

Se utiliza PostgreSQL como base de datos para leer la información de la serie de tiempo construida por ArcSWAT.

En https://github.com/berenice1997/Guerrero-PSO-code.git se puede acceder al código fuente usado para la implementación del problema.