Multi-objective particle swarm optimization for environmental risk/benefit analysis with pre-assignment strategy

Luca Puzzoli[1], Gabriele Sbaiz[2] and Luca Manzoni[1]

[1]Department of Mathematics, Informatics and Geosciences, University of Trieste, Via Valerio 12/1, 34127 Trieste, Italy
[2]Department of Economics, Business, Mathematics and Statistics, University of Trieste, Via Valerio 4/1, 34127 Trieste, Italy

Abstract
Hydropower is a fundamental renewable energy source, and the Amazon basin represents one of its largest untapped frontiers. However, its expansion in this ecologically sensitive region raises significant environmental challenges, especially concerning greenhouse gas emissions. In this paper, we develop a multi-objective optimization framework that employs a variant of the Multi-Objective Particle Swarm Optimizer to balance the competing objectives represented by the total electricity generation and the reduction of carbon emissions. We analyse a dataset of 509 dams, categorized by geographical and technical features, to assess the impact of site selection and taking into account the pre-assignment of dams already installed. We further inspect the key features of dams that compose the best configurations to maximize energy output while minimizing emissions. In such configurations, the dams are located in highland areas, offering flexible trade-offs and allowing planners to balance sustainability with energy demands. Decision-makers could take advantage of this work by adopting a strategic approach to hydropower expansion that prioritizes energy efficiency and environmental responsibility, showcasing the effectiveness of computational optimization in sustainable energy planning.

Keywords
Multi-objective optimization problems, Multi-objective PSO, Risk/benefit analysis, Dams strategic plans with pre-assignment.

1. Introduction

In this work we address the strategic planning of dams for hydropower development in the Amazon basin, with the dual objectives of maximizing electricity generation and minimizing greenhouse gas (GHG) emissions. If hydropower expansion proceeds without strategic planning, particularly in lowland areas that require large reservoirs, it could lead to substantial GHG emissions, due to the decomposition of flooded organic material. These emissions reduce the climate benefits of hydropower and contribute to global warming. Conversely, a carefully coordinated approach that prioritizes dam placement in higher elevation areas with smaller reservoirs and higher power densities could significantly reduce emissions while still ensuring renewable energy generation. The urgency of addressing this issue is driven by the need to balance electricity generation with the necessity to minimize GHG emissions. This is particularly critical in the context of global climate mitigation efforts, as outlined in the IPCC Special Report [1]. The goal is to optimize dam locations and configurations to maximize electricity generation while minimizing environmental impacts. This necessitates the use of a multi-objective optimization framework to evaluate trade-offs between energy production and carbon emissions. To tackle this problem we employ a variant of the Multi-Objective Particle Swarm Optimization (MOPSO) algorithm. Extending PSO to multi-objective optimization problems was initially presented in [2], where it has been shown that swarm-based approaches can handle conflicting objectives effectively, laying the foundation for later adaptations. Later, in [3] the authors have introduced a MOPSO algorithm incorporating Pareto dominance and an external archive to maintain solution diversity and improve convergence. In [4] the authors have investigated the impact of key parameters on MOPSO performance, showing that the

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luca.puzzoli@studenti.units.it (L. Puzzoli); gabriele.sbaiz@deams.units.it (G. Sbaiz); lmanzoni@units.it (L. Manzoni)
0000-0003-3500-6843 (G. Sbaiz); 0000-0001-6312-7728 (L. Manzoni)

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inertia weight plays a crucial role in balancing exploration and exploitation. Finally, in [5], the authors have provided a detailed review of MOPSO advancements, categorizing modifications based on leader selection, archive management and velocity updates. The paper is structured as follows: in the next section we introduce the mathematical model and we describe the developed variant of the MOPSO. In Section 3 we present the results and Section 4 concludes.

2. Mathematical model and solver

This study presents a multi-objective optimization problem that seeks to balance two conflicting objectives. More specifically,

$$\max_{x \in [0,1]^n} \Big(f_1(x),\ -f_2(x) \Big)$$

where

$$f_1(x) = \sum_{i \in S(x)} \mathrm{EG}_i, \quad \text{and} \quad f_2(x) = \sum_{i \in S(x)} \mathrm{CI}_i,$$

subject to $S(x) = \{i \mid x_i > 0.5\}$ and $x_i \in [0,1], \forall i \in \{1, \dots, n\}$. Each potential solution is expressed by a decision vector $x = (x_1, \dots, x_n) \in [0,1]^n$, representing the selection probability of each dam, based on a predefined threshold. The first objective function aims to maximize the total electricity generation (EG) from the selected dams. This function sums the electricity generation contributions from all selected dams, aiming to maximize the total energy output. The second objective function, instead, seeks to minimize the total carbon intensity (CI) associated with the selected energy sources.

Remark 1. *It is worth noting that we introduce a pre-assignment strategy in the decision-making process, i.e. the dams already installed are incorporated in all the candidate solutions since such dams are excluded from the optimization task.*

Since these objectives are conflicting, to solve this multi-objective optimization problem, we employ the MOPSO solver which is a PSO variant able to produce the Pareto front efficiently. After some comparison results with different variants of MOPSO, we have chosen for our analysis the MOPSO-based algorithm where we introduce a linearly decreasing inertia weight to encourage an adaptive balance between exploration and exploitation. The inertia weight starts at 0.9 and gradually decreases to 0.4 as the iterations progress. In this model, the social and cognitive coefficients are kept constant at 1.49 to isolate the impact of inertia weight variation (see [6]). The population size is set to 1,000 particles, and the number of iterations is fixed at 400. Finally, the archive size is set to 300 particles and the MOPSO is executed 30 times independently, with each run initialized using a different randomly generated swarm.

3. Experimental analysis

We consider a dataset in which there are accounted a total of 509 dams, categorized in 351 proposed and 158 existing. It is worth noticing that the 158 installed dams are pre-assigned in the optimization, i.e. they are not involved in the decision-making process. These data are provided in [7], accordingly with information from national government databases for countries, where updated inventory data are readily available. In details, for both proposed and existing dams, the dataset comprehends geographic location, country and region (upland/lowland), elevation and technical data including installed capacity. The alluvial diagram, reported in Figure 2, represents the evolution of dam selections across multiple Pareto optimal solutions of a selected run computed by MOPSO (see Figure 1). Each node in the diagram corresponds to a specific solution along the Pareto front, representing a unique configuration of selected dams. The nodes are positioned sequentially, showing the transition from one solution to the next. By analysing these transitions, we can assess whether the Pareto optimal solutions exhibit stability, where

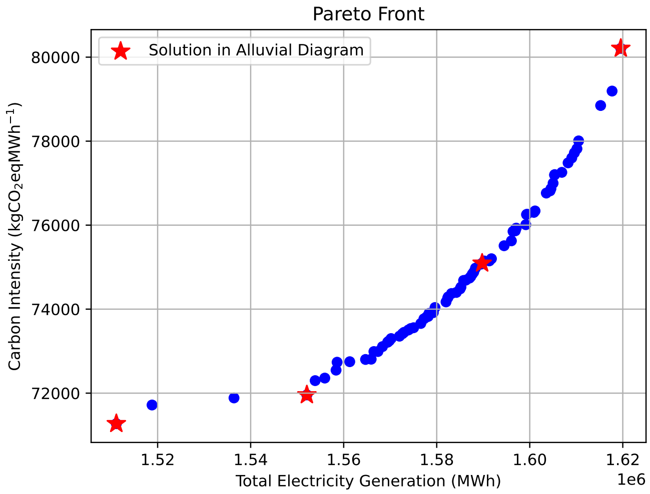

Figure 1: Pareto front of a selected run.

the same dams are consistently selected, or variation, where significant modifications occur in dam selection. The presence of wide flows in Figure 2 for the "Selected" dams suggests a core set of dams that frequently appear across multiple solutions, indicating their essential role in balancing electricity production and carbon intensity. Analogously, wide flows for the "Discarded" dams indicate dams that are either never selected among the solutions or were introduced but later removed, suggesting an unstable selection pattern. Therefore, these dams do not consistently contribute to optimal trade-offs and are instead subject to repeated inclusion and exclusion as the Pareto front evolves. In general, the

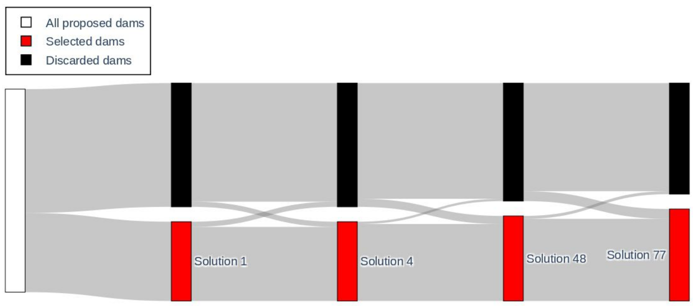

Figure 2: Alluvial diagram for selected solutions.

previous results show that the core of the efficient dams (in terms of energy production and climate impact) is solid as well as the pool of the inefficient ones. This implies a well-founded starting point for the discussion of decision-makers in order to choose the dams to be built to meet the increasing demand for energy or sustainability.

To further analyse the composition of solutions, we employ the Jaccard similarity measure [8], which quantifies the degree of overlap between different Pareto optimal solutions. This method helps to identify clusters of similar configurations, indicating whether solutions share common dams, suggesting their central role in the optimization. Figure 3 illustrates the Jaccard distance between consecutive Pareto optimal solutions as a function of total electricity production. In particular, the x-axis represents total electricity generation, measured in millions of units (1e6) of MWh, while the y-axis quantifies the Jaccard distance, which measures the dissimilarity between successive sets of dams. A higher Jaccard distance indicates a greater structural difference among adjacent solutions, whereas lower values suggest that consecutive sets share many common elements.

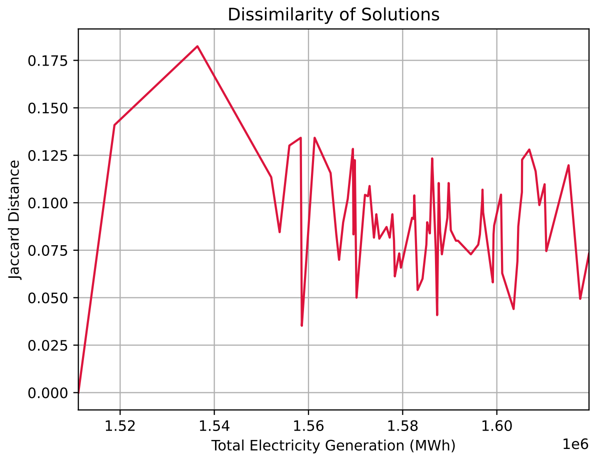

Figure 3: Jaccard distance for a selected run of MOPSO.

Finally, to extend the previous analysis, we inspect the whole pairwise comparison of solutions in the Pareto front by constructing the Jaccard distance matrix [9]. This approach allows us to move beyond consecutive comparisons and identify the structural relationships among all solutions obtained in the selected run computed by MOPSO, simultaneously (see Figure 4). Specifically, the x-axis and y-axis represent the index of the solutions in the Pareto front. Each entry in the matrix quantifies the Jaccard distance between two solutions, with darker regions indicating higher distances (greater dissimilarity) and lighter regions corresponding to lower distances (greater similarity).

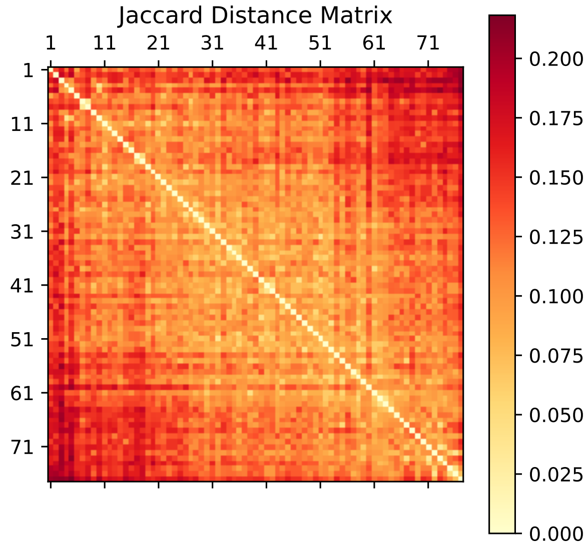

Figure 4: Jaccard matrix for a selected run.

The observed fluctuations for the Jaccard distance in Figure 3 reveal distinct patterns in the composition of solutions across the Pareto front. In some regions of the plot, the Jaccard distance remains relatively small, indicating that consecutive solutions share a significant number of dams, allowing for gradual adjustments. This suggests that modifications without drastic set restructuring, such as minor reallocation of dams, are sufficient to move along the Pareto front and achieve a new optimal balance between the objective values. On the other hand, there are regions where the Jaccard distance increases more noticeably, even though it remains below 18%, showing more substantial differences in set composition between consecutive solutions. Consequently, this suggests that certain Pareto solutions require major modifications, such as replacing several dams.

Analogous considerations could be inferred from Figure 4, where the presence of lighter regions suggests clusters of solutions that share a significant number of common dams, highlighting local stability in the Pareto front. Conversely, darker areas indicate pairs of solutions with higher Jaccard distances, signifying substantial structural differences in solution composition.

Remark 2. *Similar patterns are present in the optimization problem, where all the dams are involved in the decision-making process. However, those results show better trade-offs between energy production and environmental impact. As a consequence, it appears evident that some installed dams are completely inefficient and should be deactivated (see [10] in this respect).*

4. Conclusions

This study has addressed the strategic planning of hydropower expansion in the Amazon basin with a pre-assignment strategy. To tackle this challenge, we have developed a multi-objective optimization framework that explores the trade-offs between energy production and carbon emissions. Using MOPSO, we have identified Pareto optimal dam configurations that balance these competing objectives. Additionally, this study has investigated the potential of proposed dams, evaluating whether they should be constructed, or activated, or not. The findings could contribute to the broader discussion on renewable energy planning, highlighting the importance of strategic site selection in reducing environmental impacts while maximizing energy efficiency.

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Declaration on Generative AI

The author(s) have not employed any Generative AI tools.

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