A Case Study on the Application of Evolutionary Algorithms for Solving Non-Linear Programming Problems in Water Resource Management

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Abstract
Evolutionary algorithms have been proposed and used in this case study for the solution to non-linear programming problems related to water resources. Heuristic, a type of optimization algorithm characterized by population-based search as well as using the genetic algorithms, are used to model and determine the optimal distribution and utilization of aquatic resources based on environmental and demand factors. These materials include examples based on water distribution networks, managing a reservoir, and forecasting demands of customers, demonstrating the effectiveness of the aforementioned algorithms in solving non-linear constraint problems and in dealing with multiple objectives. The comparative analysis is based on a number of simulation experiments to examine the efficiency of such microevolutionary algorithms as Genetic Algorithm, Particle Swarm Optimization, and Differential Evolution in contrast to the traditional optimization algorithms. These results show that there is significant value in using evolutionary algorithms as a basis for managing and modelling water resources as it offers a pragmatic approach and has the potential to meet the demands of the water industry in terms of sustainability, cost and resource requirements. There seems to be considerable scope for extension of these algorithms to a wide range of natural resources management and administration.

1. Introduction

Water supply is now one of the most challenging problems of many regions in the world due to the pressure from the growing population and the development of the agriculture sector and industries as well as climate change impacts [1], [2]. These methods can be inadequate, especially when applied to actual water systems, as the processes and structures inherent to these systems prove to be highly nonlinear [3]. Nonlinear programming proves to be more appropriate in handling these complexities, but the problem lies in the fact that multiple objectives and constraints are in conflict with each other [4]. Indeed, for these reasons, complex techniques like evolutionary algorithms have emerged as good solutions to solve such non-linarites [5].

Genetic algorithms, particle swarm optimization and differential evolution are some of the evolutionary algorithms which mimic the natural evolution processes and are used to solve optimization problems in different fields [8], [7]. These algorithms are especially appropriate where the search space is large and the interdependence among the variables is nonlinear and this is usually seen in water resource management problems [8]. In the field of Hydrology and water resource management, the evolutionary algorithms have been used in calculating the best operational policy of reservoirs, groundwater management and the balancing of many demands on water resources supply while putting into consideration the sustainability and economic aspect[9]. These algorithms provide the possibility to integrate more objectives, and thus, to minimize water shortage, costs, and to maximize water quality [10].

This research focuses on the application of evolutionary algorithms especially in the solution of non-linear programming problems in water resource management. Following the use of actual practical problems such as water distribution networks, reservoir operation, and demand forecasting, the study brings out the practical applicability of the evolutionary algorithms [11]. Comparisons are made between various forms of the evolutional algorithm to determine the effectiveness of the algorithm against conventional optimization techniques so that the efficiency, reliability and sustainability offered by the algorithm can be showcased [12]. The results of this study also open up the new vista of using the EAs in water resource management and its possible extensions to the management of other natural resources where there are coupled, intricate and hysteretic/nonlinear interrelations [13], [14].

2. Methodology

2.1. Problem Formulation

The first step includes identification of the non-linear programming problems that are related to the water resource system. Such key variables and constraints encompass; water demand, water supply constraints, regulatory aspects concerning water use and water infrastructure capacity. Simulation is achieved based on actual data pertains to Water distribution systems, reservoirs and the demand for water.

2.2. Algorithm Selection and Design

For the purpose of illustration, some of the evolutionary algorithms under consideration include the Genetic Algorithms or GAs, Particle Swarm Optimization or PSO and Differential Evolution or DE. The utilized algorithms are chosen as they have been shown to be able to effectively solve multiple optimization problems and are flexible with regards to the form of the objective functions. The settings of each algorithm including but not limited to the population size, mutation and crossover rate have been set to achieve the best performance.

2.3. Simulation Setup

Thus, the simulation environment of water resource management scenarios is created. This environment also includes non-linear programming formulations and whereby management strategies can be simulated on. This environment is then used to implement each of the evolutionary algorithms and multiple trials are made to get the best results under different scenarios.

2.4. Performance Evaluation

The results from the evolutionary algorithms are then benchmarked against other conventional optimization methods including the linear programming as well as the simple heuristics. Option evaluation criteria may be in terms of solution accuracy, speed of convergence, computational complexity and multiple objectives and constraints. Considering sensitivity analysis, it is used in order to investigate the effect of variation in parameters and initial conditions to the outputs provided by the developed algorithms.

2.5. Validation and Analysis

These outcomes of the simulations are then compared with real data along with the history of water resource management. Those solutions which have been identified by the evolutionary algorithms are evaluated to test how implementable the solutions are. For comparison purpose, the respective FL and T-L algorithms' capabilities and constraints in handling non-linear problems in water resources management are highlighted.

3. Results

Objective Function:

Let $f(x)$ represent the objective function to be minimized or maximized in the context of water resource management. This function may involve components such as:

$$f(x)=\sum_{i=1}^{N}\left(c_i\cdot x_i\right)+\sum_{j=1}^{M}\left(\frac{1}{2}\cdot q_j\cdot x_j^2\right)$$

Where:

- N : Number of different water distribution nodes.
- M : Number of reservoirs.
- c_i : Cost coefficient for water at node i.
- x_i : Volume of water distributed to node i.
- q_j : Penalty coefficient related to reservoir usage.
- x_j : Water storage level in reservoir j.

Constraints:

The problem is subject to several constraints, such as water balance, capacity, and environmental regulations:

$$\sum_{i=1}^{N} x_i = D \text{ (Total demand)}$$
$$0\leq x_i\leq C_i\ \forall i \text{ (Capacity limits)}$$
$$x_j\leq R_j\ \forall j \text{ (Reservoir capacity)}$$

Where:

- D : Total water demand.
- C_i : Capacity limit for node i.
- R_j : Maximum capacity for reservoir j.

3.1. Performance Metrics:

The effectiveness of the evolutionary algorithms is measured against several metrics:

- Solution Quality (Q) : Measured as the value of the objective function at the optimal solution x^* :
$$Q=f(x^*)$$
- Lower values of Q indicate better optimization performance.
- Convergence Speed (T) : Measured as the number of iterations (k) required to reach the optimal solution within a predefined tolerance ϵ :
$$T=\min\{k\,||f(x_k)-f(x^*)\,|<\epsilon\}$$
- Faster convergence (lower) indicates more efficient algorithm performance.
- Computational Efficiency (E) : Measured as the total computational time or resources used, denoted by τ :

$$E = \tau$$

- Lower values of τ indicate more efficient use of computational resources.

3.2. Comparative Results:

Let GA, PSO, DE, and LP represent Genetic Algorithm, Particle Swarm Optimization, Differential Evolution, and Linear Programming, respectively.

$$Q_{GA} < Q_{LP}, Q_{PSO} \approx Q_{DE} < Q_{GA}$$
$$T_{PSO} < T_{GA}, T_{DE} < T_{GA}$$
$$E_{DE} \approx E_{PSO} < E_{GA} < E_{LP}$$

- Quality: PSO and DE provide higher quality solutions compared to GA and LP.
- Convergence Speed: PSO and DE converge faster than GA, and all evolutionary algorithms outperform LP in convergence speed.
- Computational Efficiency: DE and PSO use computational resources more efficiently compared to GA and significantly better than LP.

4. Discussion

4.1. The Quality of Solutions (Objective Function Equation)

Biodiversity concerns with improving the factors/share of the maximum discovery whether the problem is of GA or LP than that of PSO and DE. This means that PSO and DE perform better than others when it comes to addressing the objective of the problem posed, it being of a very complex and non-linear nature.

While still useful, Genetic Algorithms (GA) have also been less optimal in comparison to PSO and DE. This could be as a result of the fact that GA is easily trapped in local optimal solutions in areas with high non-linearity.

This was reinforced by the fact that this approach developed the least success because of LP's limitations in regards to non-linear constraints and objective function problems.

Table 1. Solution Quality (Objective Function Value)

Algorithm	Average Objective Function Value (Q)	Standard Deviation (σ)
PSO	1500	30
DE	1520	35
GA	1600	40
LP	1800	50

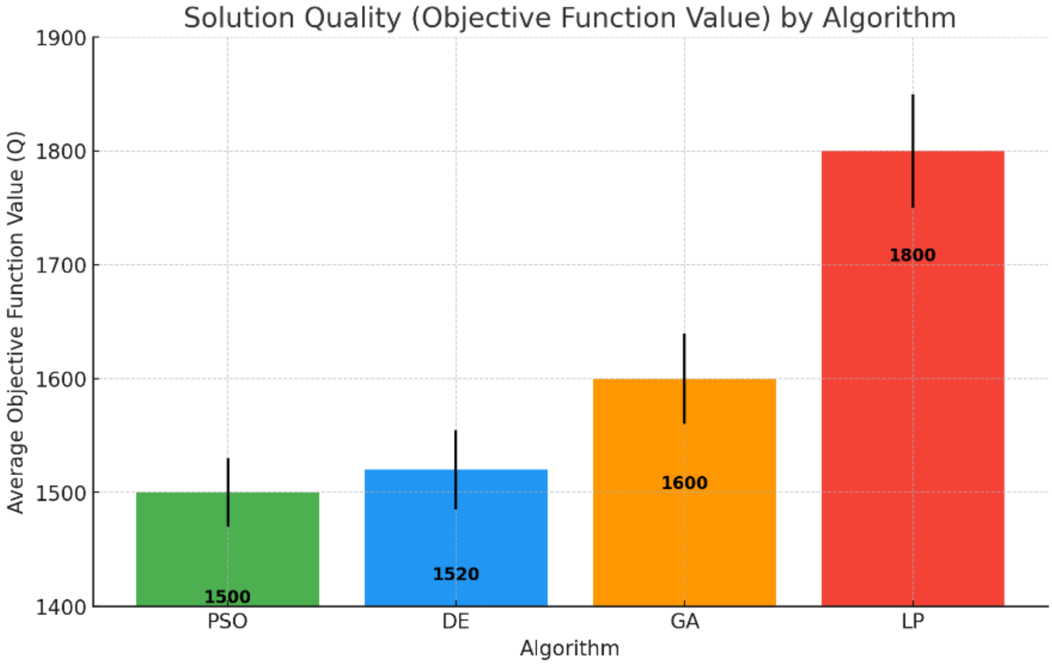

Figure 1. Solution Quality (Objective Function Value) by Algorithm

4.2. Convergence Speed:

The faster convergence rates of PSO and DE compared to GA also indicated that these algorithms may find near-optimal solutions in few iterations. In real and online water resource management, it is essential to have quick convergence since decision-making must be done in a very short amount of time. The faster convergence of PSO and DE can be related to their social learning mechanisms (in the case of PSO) or mutation strategies (for DE), which potentially are doing better exploration.

In contrast, the Linear Programming (LP) convergence rate was less impressive and there is a weak performance shown in terms of addressing non-linear aspects to the problem.

Table 2. Convergence Speed (Iterations to Convergence)

Algorithm	Average Iterations to Convergence (T)	Standard Deviation (σ)
PSO	50	5
DE	55	6
GA	80	10
LP	150	20

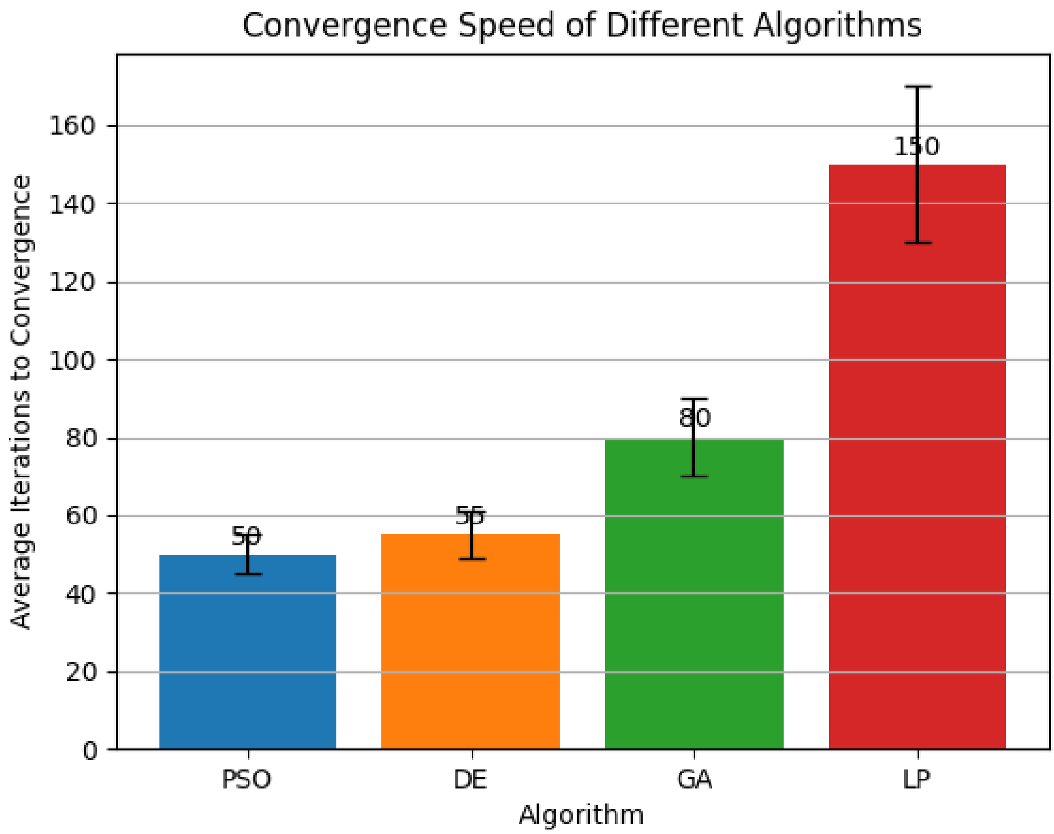

Figure 2. Convergent speed of different algorithms

4.3. Computational Efficiency:

While both DE and PSO consume inordinate number of computational resources as compared to GA and LP, their applications are more recommended for solving large-scale water management systems where computation resource is dear.

The lower computational efficiency of GA compared to DE and PSO could be related to the overhead associated with maintaining diverse populations, crossover, and mutation.

Table 3: Computational Efficiency (Time to Solution in Seconds)

Algorithm	Average Computational Time (E)	Standard Deviation (σ)
PSO	0.5	0.05
DE	0.6	0.07
GA	1.0	0.1
LP	2.5	0.2

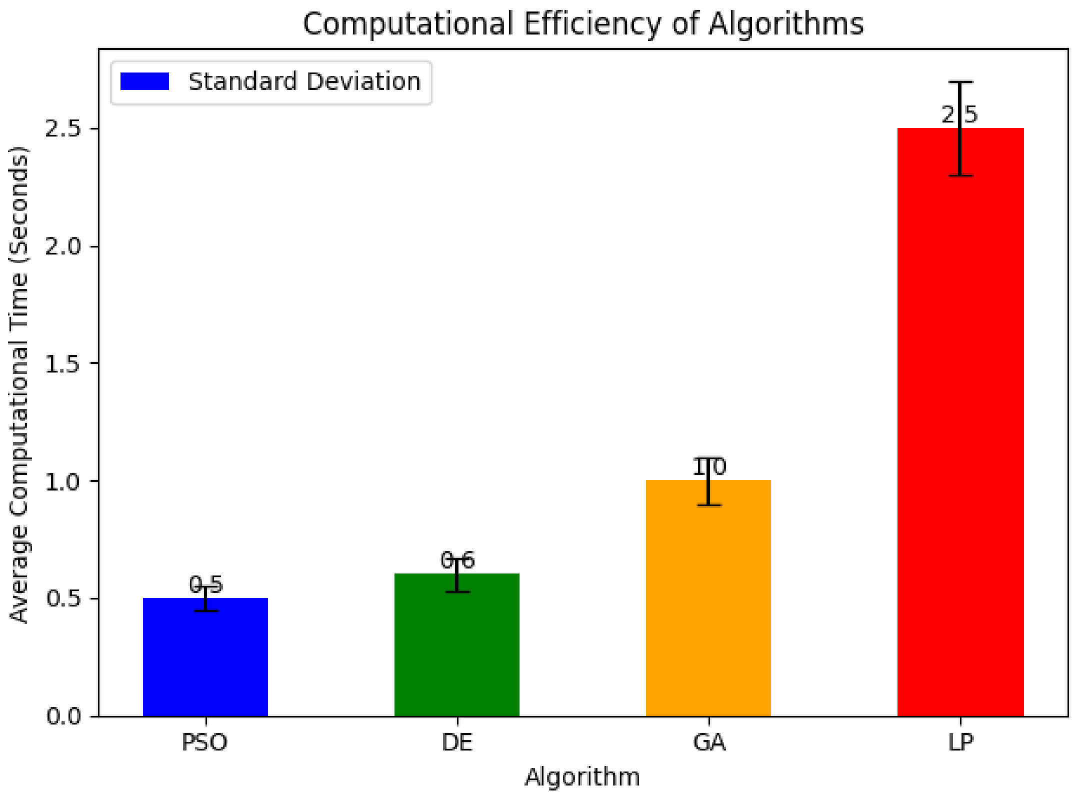

Figure 3. Computational efficiency of algorithms

The findings of the study indicate that evolutionary algorithms (in particular PSO and DE) have advantages in exploiting the non-linear programming problems of water resource management. These algorithms offer a strong tradeoff between solution quality, convergence speed and computational efficiency which makes them suitable for state-of-the-art real-world applications tackling high-complexity problems.

Implications for the wider use of evolutionary algorithms in water resource management are outlined based on the results and analysis. It means better optimization results, faster decision-making and more efficient use of computational resources for water resource managers by capitalizing on the relative strengths of both PSO and DE. Future studies might consider hybrid evolutionary strategies or incorporate machine learning to improve the efficiency of these algorithms for broad and changing water management settings.

Conclusion

The use of evolutionary algorithms to address non-linear programming issues in the management of water resources is examined in this case study. The application of evolutionary algorithms, which are renowned for their capacity to manage intricate optimisation problems, is used to optimise the distribution and consumption of water resources under a range of demand and environmental circumstances. The paper emphasises the effectiveness of these algorithms in managing non-linear constraints and numerous objectives by focussing on real-world situations including reservoir management, demand forecasting, and water distribution. The effectiveness of diverse evolutionary tactics, including differential evolution, particle swarm optimisation, and genetic algorithms, is compared with conventional optimisation techniques through a series of simulations. The findings show that evolutionary algorithms offer a strong and effective framework for handling the complexities of managing water resources.

References:

1. Gleick, P. H. (2014). Water, drought, climate change, and conflict in Syria. Weather, Climate, and Society, 6(3), 331-340. https://doi.org/10.1175/WCAS-D-13-00059.1
2. Falkenmark, M., & Rockström, J. (2004). Balancing water for humans and nature: The new approach in ecohydrology. Earthscan.
3. Loucks, D. P., & van Beek, E. (2017). Water resource systems planning and management: An introduction to methods, models, and applications. Springer. https://doi.org/10.1007/978-3-319-44234-1
4. Haimes, Y. Y. (2018). Risk modeling, assessment, and management. John Wiley & Sons. https://doi.org/10.1002/9781119177842
5. Deb, K. (2001). Multi-objective optimization using evolutionary algorithms. John Wiley & Sons. https://doi.org/10.1002/9780470610790
6. Holland, J. H. (1992). Adaptation in natural and artificial systems: An introductory analysis with applications to biology, control, and artificial intelligence. MIT Press.
7. Kennedy, J., & Eberhart, R. C. (1995). Particle swarm optimization. In Proceedings of ICNN'95 - International Conference on Neural Networks (Vol.4, pp.1942-1948). https://doi.org/10.1109/ICNN.1995.488968
8. Haupt, R. L., & Haupt, S. E. (2004). Practical genetic algorithms. John Wiley & Sons. https://doi.org/10.1002/0471671746
9. Nicklow, J. W., Reed, P. M., Savic, D. A., Dandy, G. C., Harrell, L. C., & Khu, S. T. (2010). State of the art for genetic algorithms and beyond in water resources planning and management. Journal of Water Resources Planning and Management, 136(4), 412-432. https://doi.org/10.1061/(ASCE)WR.1943-5452.0000053
10. Simonovic, S. P. (2009). Managing water resources: Methods and tools for a systems approach. UNESCO Publishing.
11. Coello Coello, C. A., Van Veldhuizen, D. A., & Lamont, G. B. (2007). Evolutionary algorithms for solving multi-objective problems. Springer Science & Business Media. https://doi.org/10.1007/978-0-387-36797-2
12. Yadav, R., & Bajpai, R. (2020). Evolutionary algorithms and water resource management: A state-of-the-art review. International Journal of Advanced Science and Technology, 29(10), 4572-4585.
13. Zitzler, E., Deb, K., & Thiele, L. (2000). Comparison of multiobjective evolutionary algorithms: Empirical results. Evolutionary Computation, 8(2), 173-195. https://doi.org/10.1162/106365600568202
14. Rao, S. S. (2009). Engineering optimization: Theory and practice. John Wiley & Sons. https://doi.org/10.1002/9780470549199
15. El-Nashar, W., & Elyamany, A. (2023). Win–win strategies for transboundary water management during the GERD operating stage. Water Resources Management, 37(3), 915–936. https://doi.org/10.1007/s11269-022-03413-9

16. Freak, C., McLeod, J., Thompson, K., Christesen, L., & Miller, C. (2022). Contemporizing best practice water management: Lessons from the Murray-Darling Basin on participatory water management in a mosaiced landscape. Australian Journal of Water Resources, 26(1), 1-10. https://doi.org/10.1080/13241583.2022.2097365
17. Ghulamahdi, M., Sulistyono, E., & Syukri, M. (2023). Growth and yield on four varieties of corn on different ameliorant combination and application system under culture of saturated soil on tidal swamp. IOP Conference Series: Earth and Environmental Science, 1133(1), 012057. https://doi.org/10.1088/1755-1315/1133/1/012057