HYDROSYSTEM OPTIMIZATION ON A BUDGET: INVESTIGATING THE POTENTIAL OF SURROGATE BASED OPTIMIZATION TECHNIQUES

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ABSTRACT

Development of uncertainty-aware operational rules for multi-reservoir systems is a demanding and challenging task due to the complexity of the system dynamics, the number of decision variables and the hydrological uncertainty. In order to overcome this issue the parsimonious parameterization-simulation-optimization (PSO) framework is employed coupled with stochastically generated hydrological time-series. However, when the simulation model requires long computational time this coupling imposes a computational barrier to the framework. The purpose of this paper is threefold: a) Investigate the potential of Efficient Global Optimization (EGO) algorithm (and its variants) which is capable of reaching global optima within a few simulation model evaluations (~500 or less). b) Extend the capabilities of WEAP21 water resources management model by using it within PSO framework (named WEAP21-PSO) and c) Validate and compare the results of WEAP21-PSO using the well-known hydrosystem management model Hydronomeas coupled with Evolutionary Annealing Simplex (EAS) optimization algorithm. Results confirm that EGO has the potential and the capabilities to handle computationally demanding problems and furthermore is capable of locating the optimal solution within few simulation model evaluations and that the WEAP21-PSO framework performs well at the task at hand.

Keywords: Multi-reservoir system management, Parameterization-Simulation-Optimization (PSO) framework, Efficient Global Optimization (EGO) algorithm, WEAP21, MATLAB

1. Introduction

Operation of large-scale reservoir systems is a complex problem that involves a number of conflicting objectives, such as hydropower generation, water supply, etc. Finding the optimal operational policy is a challenging task due to the non-linearity of the system dynamics and the uncertainty of future inflows and water demands. Thus, necessitating a systemic approach to decision making. Consequently, it is important to develop a holistic framework based on stochastic simulation and optimization [1]. Parameterization-Simulation-Optimization (PSO) framework proposed by [2] effectively addresses uncertainty by coupling stochastic simulation (via long synthetically generated timeseries) to drive the simulation-optimization process and hence develop risk-based, uncertainty-aware reservoir operational rules. However, the use of long timeseries directly increases the computational effort required by the simulation model and thus by the optimization process. In this paper we investigate the potential of Efficient Global Optimization (EGO) algorithm [3], which is a Surrogate Based Optimization (SBO) approach. In order to assess the algorithm we couple WEAP21 water resources management model [4] with MATLAB and thus extend its capabilities by using it within PSO framework (named WEAP21-PSO). The simulation part is performed in WEAP21, while the optimization part is implemented in MATLAB. Within the same context multiple optimization trials of three optimization algorithms are performed. Namely, EGO, Simulated Annealing [SA - 5] and Evolutionary Annealing Simplex algorithm [EAS - 6]. In order to validate and assess the results, the hydrosystem of Aliakmonas in Greece is modeled, using the same assumptions in both WEAP21-PSO and Hydronomeas decision support system (DSS) [7] the latter is using EAS as built-in optimization algorithm.

2. Methodology

2.1. Conceptual Parameterization-Simulation-Optimization approach

This work employs the single-objective Parameterization-Simulation-Optimization (PSO) framework [2] which was recently extended to handle multiple objectives [8]. Among the advantages of PSO over other similar methods (e.g., implicit stochastic optimization and explicit stochastic optimization) are the parameter-parsimonious character, the incorporation of hydrological uncertainty and the simplicity of the resulting operational rules. PSO consists of the following steps: 1) Representation of the main hydrological components (precipitation, evapotranspiration, inflow) through stochastic simulation, by using stochastic simulation models to generate long synthetic timeseries able to capture and reproduce the statistical properties of the historical sample. This way the hydrological uncertainty is embedded and allows the determination of safe and robust conclusions about the performance and reliability of the test hydrosystem [9]. 2) Parameterization of the operational rules of the reservoirs system via a small number of parameters θ. 3) Simulation of the hydrosystem using the synthetic timeseries and 4) Definition of appropriate objective function(s) that express the desired performance metric(s). 5) Utilization of an optimization algorithm to derive the best managerial policy. In this work, one objective function related to hydro-energy production has been employed.

In order to express the hydropower policy, suitable control variables θ and performance measures (objective functions) should be specified. Regarding parameterization of the operational rules of the hydrosystem, a parsimonious approach is employed. Each turbine and pump (*n)* component of the system is parameterized by 1 variable ($\theta_1,\ldots,\theta_n$) referring to constant hydropower generation or pumping target respectively. Regarding the performance measure the objective was the maximization of firm energy [10], which is the monthly energy that can be guaranteed from the reservoir system for certain reliability level (e.g., reliability a = 99%), the energy produced above firm is called secondary or excessive energy. The computation of the objective function is as follows:

$$\textbf{Objective function: } \arg\max\{E^c\}, \tag{1}$$

$$\textbf{s.t.} \quad a = P(E(t) > E^c) = n^s / n^{tot} = 99\%, \tag{2}$$

where, $E(t) = \sum_{i=1}^{n} E_i(t)$, *E(t)* is the hydropower energy time-series for given θ_i, for $t=1,\ldots,n^{tot}$, where n^{tot} is the total number of time-steps for all months and all years in simulation. While, $i=1\ldots n$, n denotes the number of hydropower reservoirs. E^c denotes the firm energy of the system for the whole simulation period, and a the desired reliability (= 99%), calculated by dividing n^s and n^{tot}, where n^s is the number of time-steps that exceed $E(t) > E^c$ and n^{tot} is the total number of time-steps in *E(t)*.

2.2. Efficient Global Optimization (EGO) algorithm

The key idea behind EGO [3] (and other SBO algorithms) is to replace most of objective function (OF) evaluations (or simulation model) with a surrogate model (SM). In general SBO algorithms are particularly useful when the OF is expensive to evaluate in terms of time and/or computational effort required. An extensive review of SBO is given by [11]. The first step of EGO is to capture some information about the response of the OF using Design of Experiments (DoE) methods [12]. Subsequently the SM is built based on the sampling plan. The next step is to optimize the SM using Expected Improvement (EI, eq. 4) in order to identify potential points to evaluate with the OF. After the new sample point is selected and evaluated with the OF, the SM is updated and the iterative process continues until the number of maximum function evaluations is reached. EGO uses Kriging [13] as SM; which has gained a lot of attention after the publication of [14] in approximation of deterministic computer experiments. Kriging model consists of two terms: the first is a global model (trend function) that interpolates all design points, while the second represent "localized" functions expressing the deviations (departure) from the global model at all points. The approximated response is expressed as:

$$\hat{y}(\boldsymbol{x}) = f(\boldsymbol{x}) + Z(\boldsymbol{x}) \tag{3}$$

The first term is a regression function *f(**x**)* and the second is a centered Gaussian process *Z(**x**)* with zero mean and variance σ^2. In our particular interest is the case where *f(**x**)* is constant and unknown; which was also suggested by [3] when there is no *prior* knowledge of the trend function; this version of Kriging is known as Ordinary Kriging (OK). The mathematical background of Kriging is presented in [11]. When dealing with OK; equation (4) can be viewed as random field with mean β. The covariance of *Z(**x**)* is given by $Cov(\mathrm{Z}) = \sigma^2 \Psi(\mathbf{x^i}, \mathbf{x^j})$ where $\Psi(\mathbf{x^i}, \mathbf{x^j})$ is an *n x n* correlation matrix. In this work the elements of that matrix are given by the generalized exponential correlation function $\Psi(\mathbf{x^i}, \mathbf{x^j}) = \exp\left[-d\left(\mathbf{x^i}, \mathbf{x^j}\right)\right]$ where, $d\left(\mathbf{x^i}, \mathbf{x^j}\right) = \sum_{m=1}^{k} \theta_m \left[\left|\mathbf{x_m^i}, \mathbf{x_m^j}\right|^p\right]$, *i* and *j* denote the training points, *m* the design parameter, *k* is the number of total design parameters, θ and *p* ($0 < p < 2$) are the hyperparameters of correlation function. To ensure the best fit of the model [11, 14], θ and *p*, are identified with Maximum Likelihood Estimation (MLE) method. After the SM is built, the SM is optimized using (EI). The evaluation of EI is based on the following equation:

$$E[I(x)] = \begin{cases} (y_{\min} - \hat{y}(x))\Phi\left(\dfrac{y_{\min} - \hat{y}(x)}{\hat{s}(x)}\right) + \hat{s}\varphi\left(\dfrac{y_{\min} - \hat{y}(x)}{\hat{s}(x)}\right) & if\ s > 0 \\ 0 & if\ s = 0 \end{cases} \tag{4}$$

where, $\Phi(\cdot)$, $\varphi(\cdot)$ and $\hat{s}(x)$ denote the cumulative distribution function, probability density function and Kriging error respectively.

3. Study area: Aliakmonas Hydrosystem

Aliakmonas is located in Western Macedonia and is the longest river in Greece originating from Greek territory. Its headwaters are the mountains Verno, Grammos and Voio, at the country's borders with Albania, and its estuaries are in the Aegean Sea, between Thessaloniki and Katerini. The river basin extends over five prefectures (Kastoria, Grevena, Kozani, Imathia, Pieria). The hydrosystem serves multiple and conflicting uses, i.e., water supply of Thessaloniki, irrigation of Western Macedonia district, cooling of Ptolemais Power Station, hydroelectric production and environmental flow. Further details about the hydrosystem are given in [15]. In the present work, we investigate the modelling scheme of the hydrosystem containing three reservoirs: Polyfyto (360 MW), Sfikia (315 MW) and Asomata (110 MW) that are currently under operation. A conceptual schematic of the hydrosystem is shown in Figure 1.

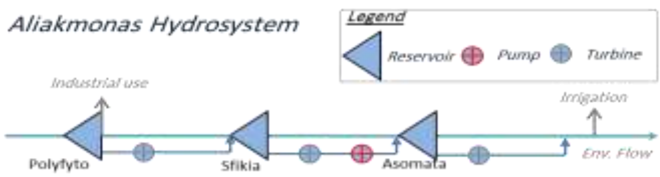

Figure 1: Schematic representation of Aliakmonas hydrosystem.

It is essential to highlight that in both approaches, namely WEAP21-PSO and Hydronomeas, we used the same assumptions, parameterization and modelling schemes (see section 2.1) as in [15]. As mentioned earlier a key component of PSO framework is the use of stochastic simulation and thus synthetic timeseries (instead of historical timeseries). More specifically, monthly synthetic timeseries of 1000-years were generated with CASTALIA software [9].

4. Results

In order to benchmark the performance EGO algorithm two evolutionary algorithms where used, simulated annealing (SA) and evolutionary annealing simplex (EAS) algorithm. Furthermore, multiple (10) independent optimization trials of each algorithm were utilized in order to safely infer about the effectiveness of the algorithms. The parameters used in EGO algorithm were briefly discussed in section 2.2 and the parameters of SA and EAS were based on [5] and [6] respectively. The initial population (or DoE) was set to 50 samples. The maximum number of function evaluations (FE) was used as termination criterion and was set to 250 FE. The results shown in Figure 2 highlight the effectiveness of EGO algorithm while there is strong evidence that the algorithm outperforms the alternative algorithms for the given computational budget of 250 FE.

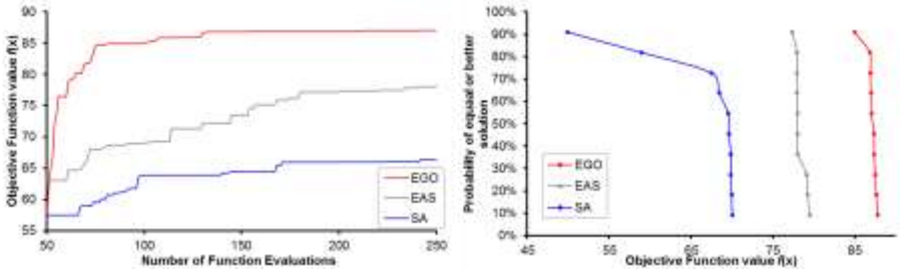

Figure 2: (Left) Average performance of algorithms relative to the number of function evaluations and (right) empirical cumulative distribution function (CDF) of best function values for 250 FE.

The left panel of Figure 2 demonstrates the average performance (of 10 trials) of the algorithms relative to the number of current FE. While the right panel of the same figure provides the emperical CDF of the algorithms. The CDFs provide a graphical interpretation of the probability of achieving an equal or better solution for a given computational budget. Overall, EGO is able to locate near-optimum parameter sets early (~150 FE) in the search procedure, while SA and EAS require higher number of FE to achieve similar results.

To validate the modelling scheme of WEAP21-PSO a comparison with Hydronomeas DSS was performed using the same input data and modelling assumptions. Figure 3 demonstrates a comparison of simulated hydropower between the two approaches using a randomly selected optimum parameter set from the results above. The selected parameter set had hydropower generation targets 18.44 GWh, 62.15 GWh and 4.04 GWh for Polyfyto, Sfikia and Asomata reservoirs respectively and the pumping target of Sfikia - Asomata pump-storage was 149 hm^3. It can be seen that both approaches simulate similar values for each individual reservoir and for the hydrosystem in total. In all cases the Pearson correlation coefficient R^2 ranges between 0.95 to 0.99.

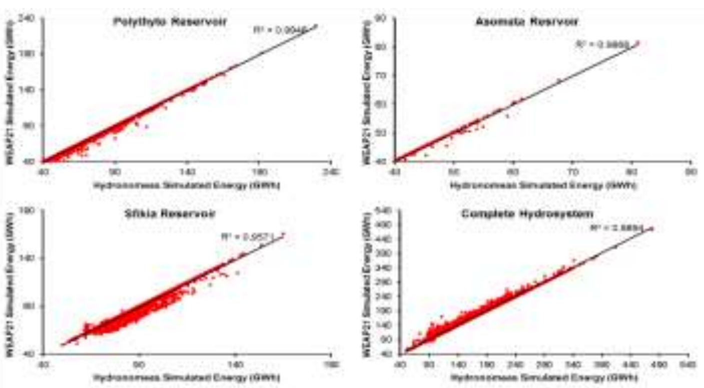

Figure 3: Comparison of hydropower generation of WEAP21-PSO and Hydronomeas for a randomly selected optimum parameter set.

Additionally, in order to thoroughly investigate the energy related behavior and properties of the multi-reservoir system, the same randomly selected optimum parameter set was used to construct the energy-duration curves (EDCs - Figure 4, left panel) of the system. The EDCs shown below demonstrate the monthly energy produced from the hydroelectric power plants for a certain percentage of time. It is worth highlighting that both WEAP21-PSO and Hydronomeas DSS simulate similar results, providing ~86 GWh with 99% reliability. This can be further validated in Figure 4 (right panel) where the monthly firm and excessive energy (secondary) is shown for both approaches.

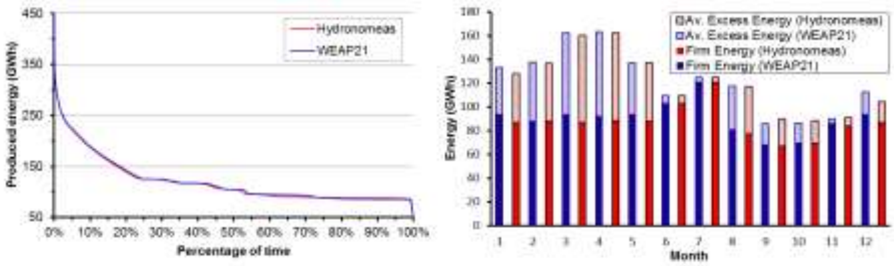

Figure 4: (Left) Energy-duration curve (right) monthly energy statistics of WEAP21-PSO and Hydronomeas for a randomly selected optimum parameter set.

5. Discussion and Conclusions

This paper investigates the effectiveness and the efficiency of EGO, a fast surrogate based optimization method. EGO algorithm demonstrates impressive results with only ~250 function evaluations when compared with other evolutionary algorithms. EGO is particular useful when the objective function is expensive (in terms of time) to evaluate or there is a budget limitation. For the optimal control of hydropower plants EGO is a fast and effective method in deriving robust uncertainty-aware optimal operational rules. The optimization criterion used in this study provided robust results related with hydroelectric energy for a given reliability level. In conclusion, WEAP21-PSO approach is validated with Hydronomeas DSS and proves to be efficient and effective through the coupling of WEAP21 with surrogate based optimization (SBO) algorithms. Within the same framework, the capabilities of WEAP21 are extended and provide robust and uncertainty-aware operational rules; this way, problems related with combined water and energy management can be effectively and practically confronted with reasonable computation effort and time.

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