Quantifying the robustness of optimal reservoir operation for the Xinanjiang-Fuchunjiang Reservoir Cascade
E. Vonk, Y. P. Xu, M. J. Booij and D. C. M. Augustijn

ABSTRACT
In this research we investigate the robustness of the common implicit stochastic optimization (ISO) method for dam reoperation. As a case study, we focus on the Xinanjiang-Fuchunjiang reservoir cascade in eastern China, for which adapted operating rules were proposed as a means to reduce the impact of climate change and socio-economic developments. The optimizations were based on five different water supply and demand scenarios for the future period from 2011 to 2040. Main uncertainties in the optimization can be traced back to correctness of the assumed supply and demand scenarios and the quality and tuning of the applied optimization algorithm. To investigate the robustness of proposed operation rules, we (1) compare cross-scenario performance of all obtained Pareto-optimal rulesets and (2) investigate whether different metaheuristic optimization algorithms lead to the same results. For the latter we compare the originally used genetic algorithm (Nondominated Sorting Genetic Algorithm II, NSGA-II) with a particle swarm optimization algorithm (MOPSO). Reservoir performance was measured using the shortage index (SI) and mean annual energy production (MAEP) as main indicators. It is found that optimal operating rules, tailored to a specific scenario, deliver at most 2.4% less hydropower when applied to a different scenario, while the SI increases at most with 0.28. NSGA-II and MOPSO are shown to yield approximately the same Pareto-front for all scenarios, even though small differences can be observed.

Key words | MOPSO, multireservoir operation, NSGA-II, optimization, robustness, scenario analysis

INTRODUCTION
There is currently a lot of attention from the scientific community to explore new methods for optimizing the long-term operation of reservoir systems (Labadie 2004). Optimization of reservoirs (and in particular multireservoir systems) is traditionally a complicated process with high computational requirements. However, recent developments have led to computationally efficient metaheuristic algorithms (MAs) that are able to optimize multireservoir systems in an integrated way. These algorithms have been applied successfully to reservoir systems with various configurations, often resulting in better operating rules than the ones currently being used (Reddy & Kumar 2007; Rani & Moreira 2010).

However, despite much attention from scientific community towards the development of efficient optimization algorithms, relatively little is known about the actual robustness of optimization results and methodologies. Labadie (2004) argued for example that many optimization models are currently not conducive to incorporating the involved risks and uncertainties and that the enormous range and varieties of optimization methods create confusion as to which to select for a particular application. Furthermore, the commonly used implicit stochastic optimization (ISO) methodology, which is actually a deterministic technique using long representative time series to account for variability in supply and demand (Rani & Moreira 2010), yields only optimal results for the period considered in the optimization.

Whenever the so called ISO methodology is used for reservoir optimization, its outcomes are typically subjected
to two major sources of uncertainty. A first source is the long-term inflow and demand records that are used as input for the optimization process. Using such records requires the assumption of hydrological and socio-economic stationarity, or at least assumes a certain development trajectory for future inflow patterns and water demand. The question arises how optimized operating rules perform in cases where the real inflow and demand patterns appear to deviate from the assumed patterns used for optimization. A second source of uncertainty is related to the quality of the MA that is being used for the optimization. Despite the great potential of metaheuristics reported in literature, many authors mention the risks of premature convergence and termination of such algorithms in local optima (Chang & Chang 2001; Fu et al. 2011).

In this study we attempt to gain more insight in the robustness aspect of ISO dam reoperation methods, thereby considering the following questions:

1. How sensitive are optimized operating rules with respect to unexpected deviations from the projected reservoir inflow and water demand?
2. How sensitive are optimization results to the type of optimization algorithm?

We investigate these two questions for the Xinanjiang-Fuchunjiang reservoir cascade, a multireservoir system located in Hangzhou Region, China. In a previous study (Vonk et al. 2014) we have studied the adjustment of reservoir operating rules as an adaptation strategy for future socio-economic developments and climate change in this region. Here, we will specifically focus on the robustness of the obtained results.

CASE STUDY

Hangzhou Region is located in Zhejiang Province (eastern China). It is a region covering about 16,850 km², containing a metropolitan area, commonly referred to as the Hangzhou urban districts, and five other districts: Fuyang City, Tonglu County, Lin'an City, Jiande City and Chun'an County. The investigated part of Hangzhou Region is located in the Qiantang River Basin.

Qiantang River has several large tributaries. The largest upstream branches, Xin'an River and Lan River, confluence in the center of the catchment and continue as Fuchun River (Figure 1). At the mouth of the river, in Hangzhou Bay, the average discharge is 1,043 m³ s⁻¹. The discharge regime is characterized by a high flow period between April and July and low flows in the remaining months.

Hangzhou Region predominantly relies on surface water from Qiantang River for its supply. Water is abstracted

![Figure 1](https://iwaponline.com/ws/article-pdf/16/1/79/413027/ws016010079.pdf)
directly from the river through various intakes. The only exception is the district Lin’an City, where groundwater is used. Two cascaded reservoirs regulate the water supply: Xianjiang Reservoir upstream and Fuchunjiang Reservoir further downstream (Figure 2). Vonk et al. (2014) explain the key design characteristics and operating rules of this reservoir system in detail.

The water supply purpose of these reservoirs competes with the currently higher prioritized flood control and hydropower generation purposes. The reservoir system is particularly suitable for our study as the surrounding region currently faces rapid population growth and economic development. These developments, in combination with climate change effects, cause an increasing stress on the water availability. Furthermore, all data relevant for this study have been monitored for an extensive period and are available for analysis.

MATERIAL AND METHODS

We used a scenario-based approach to explore the effects of various likely degrees of water stress for the future period between 2011 and 2040. Water demand was estimated by considering three underlying socio-economic drivers: rural and urban population growth, industrial production and changing land use. Climate change is considered as underlying process influencing the supply side. Projected streamflows for the future period were simulated using the GR4J rainfall-runoff model (Perrin et al. 2003). We obtained input for the hydrological simulations by dynamic downscaling of global climate simulations. The HadRM3P Regional Climate Model was employed, driven by the HadCM3 Global Circulation Model (Gordon et al. 2000). We evaluated the A2, A1B and B2 Special Report on Emissions Scenarios (SRES) greenhouse gas emission scenarios, resulting in a small, medium and large decrease of inflow to the study area, respectively. The inflow projections were combined with low, moderate and high socio-economic growth projections for water demand, resulting in five water stress scenarios: Low (L), Moderate 1 (M1), Average (A), Moderate 2 (M2) and High (H). Key statistics per scenario are shown in Table 1.

Scenario impacts were simulated with the Water Evaluation And Planning (WEAP) water allocation model (SEI 2014). This model was calibrated on 10-day historical storage volumes of Xianjiang Reservoir, 10-day releases of Fuchunjiang Reservoir and monthly hydropower production of both reservoirs for the period 1981–1990. The period 1991–2000 was selected for validation. Calibration parameters were the coefficients of the hydropower production rules. The Nash–Sutcliffe model efficiency (NSE) for the discharge downstream of Fuchunjiang Reservoir was 0.98 for the calibration period and 0.93 for the validation period. The NSE for the reservoir storage was 0.81 and 0.93 for calibration and validation, respectively. The relative error between the observed and simulated mean annual energy production (MAEP) for the calibration period was +0.5% and for the validation period +5.4%.

To derive optimal operating rules that are adapted to the various scenarios, the WEAP model was interlinked with an external optimization module (Figure 3). In the first step of this research, the Nondominated Sorting Genetic Algorithm II (NSGA-II), as proposed by Deb et al. (2002), was

Figure 2 | Xianjiang Reservoir (left) and Fuchunjiang Reservoir (right).
employed as optimization module. As this is a multiobjective optimization algorithm, it yields a set of Pareto-optimal operating rules for each scenario. Like other genetic algorithms, NSGA-II uses crossovers and mutations to improve candidate solutions iteratively. The algorithm features a so called crowding distance operator to obtain an equal spreading of solutions along the Pareto-front. NSGA-II also maintains an external repository (the elitist archive) in which the fittest candidate solutions of each iteration are stored and directly injected into the next one. We used binary tournament selection, Gaussian mutation and intermediate crossover as main settings. A real-coded scheme was used, with a mutation rate of 0.05 and crossover probability of 0.85, as recommended by Li & Wei (2008).

The population size was set to 100 individuals, with 100 iterations as the stopping criterion.

Decision variables for optimization were the coefficients of proposed linear hydropower production rules for each of the two reservoirs in the cascade, discriminating between four seasons (in total 24 target parameters). Reservoir performance was optimized by minimizing the shortage index (SI), as defined by the US Army Corps of Engineers (1997), and maximizing the MAEP. As downstream flooding and dam overtopping are not allowed within the simulation period, the flood control purpose is included as a hard constraint in the optimization.

In mathematical form the optimization problem can be stated as:

\[
\min (SI) = \min \left[ \frac{100}{N} \sum_{i=1}^{N} \left( \frac{D_i}{F_i} \right)^2 \right] \\
\max (MAEP) = \max \left[ \frac{1}{N} \sum_{i=1}^{N} (AEP_i) \right]
\]

Subject to:

\[
D_i, F_i, AEP_i = WEAP(F_i, I_j, O_j)
\]

Table 1 | Average reservoir system inflows and supply requirements (water demand and flow requirements) for the control period and the five scenarios

<table>
<thead>
<tr>
<th>Simulation</th>
<th>Average inflow (st. dev.) [BCM/year]</th>
<th>Average supply requirement (st. dev.) [BCM/year]</th>
</tr>
</thead>
<tbody>
<tr>
<td>Control period</td>
<td>28.1 (8.2)</td>
<td>13.5 (0.4)</td>
</tr>
<tr>
<td>Scenario L</td>
<td>25.4 (7.9)</td>
<td>17.8 (1.0)</td>
</tr>
<tr>
<td>Scenario M1</td>
<td>24.9 (8.5)</td>
<td>17.8 (1.0)</td>
</tr>
<tr>
<td>Scenario A</td>
<td>25.3 (7.9)</td>
<td>19.4 (2.3)</td>
</tr>
<tr>
<td>Scenario M2</td>
<td>25.4 (7.9)</td>
<td>20.3 (3.3)</td>
</tr>
<tr>
<td>Scenario H</td>
<td>24.9 (8.5)</td>
<td>20.3 (3.3)</td>
</tr>
</tbody>
</table>

Figure 3 | General setup of the ISO methodology. The optimization algorithms are interlinked with a water allocation model (WEAP), which in turn depends on the outcomes of a scenario analysis for long-term water supply and demand time series.
In these equations $N$ is the number of years in the considered study period, $D_i$ is the total shortage (deficit) in the $i$th year (water demand minus actual volume supplied) and $F_i$ is the total demand in the $i$th year. MAEP and annual energy production (AEP) are both in GWh. The indicators are subject to the constraints included in the WEAP model, which simulates with a 10-day timestep $j$. This model is based on three inputs: $F_j$, $I_j$, and $O_j$ being the water demand, inflow and operating rules in the $j$th 10-day period, respectively.

After deriving a front of Pareto-optimal solutions for each scenario using NSGA-II, we investigated the sensitivity of optimized rule sets by evaluating their cross-scenario performance. We have taken the Pareto-optimal rule set of each scenario and evaluated how it performed in the other four scenarios. By computing the average and maximum performance difference between the cross-tested rule sets and the Pareto-optimal rule set for each scenario, we get an indication of the sensitivity of rule sets to the water demand and inflow projections. To identify possible variations in the results due to inefficiencies of the optimization algorithm, we also applied a multi-objective particle swarm optimization (MOPSO) algorithm (Coello Coello et al. 2004) to the same problem and compared the results to those originally obtained with NSGA-II.

Particle swarm optimization (PSO) is inspired by the movement of social groups such as birds and fish. This social behaviour is modelled in PSO to guide a population of particles (the swarm) towards the most promising regions of the search space. As such, each particle is the representation of a candidate solution in the form of a row vector with decision variables. Each particle within a swarm is characterized by (a) its current position in the search space (determined by the solution it currently represents), (b) its velocity (position change) and (c) its personal best position visited so far (pBest). The position of each particle is updated by changing its velocity according to its own experience and that of its neighbours (Reyes-Sierra & Coello Coello 2006). The updating involves three tuneable parameters: the inertia weight (which controls the influence of a particle's previous velocity), a cognitive learning factor (representing the attraction that a particle has towards its own success) and a social learning factor (representing the attraction that a particle has towards the success of its neighbours). The MOPSO algorithm maintains an external repository to store all nondominated solutions discovered so far in the optimization process.

MOPSO has already been applied to the Three Gorges cascade reservoirs by Yang et al. (2009), who showed that the algorithm found solutions with good diversity and consistent convergence. To investigate how MOPSO compares to NSGA-II in terms of quality of the obtained results, we also apply this algorithm to the Xinanjiang-Fuchunjiang reservoir system. Similar to the settings of NSGA-II, a swarm size of 100 particles is used, with 100 iterations as stopping criterion. Following Reddy & Kumar (2007), an inertia weight of 1.0 was used, with a personal learning coefficient of 1.0, global learning coefficient of 0.5 and the constriction coefficient set at 0.9.

RESULTS AND DISCUSSION

For the investigated Xinanjiang-Fuchunjiang reservoir cascade, a re-optimization of the long-term operating rules appeared to be an effective strategy for reducing the potential impacts of climate change and regional socio-economic developments. As described in Vonk et al. (2014), adapted operating rules on average reduce the SI from 0.36 to 0.06 and increase the MAEP with 6.4% (compared to the projected future performance of conventional operation).

Cross-scenario performance of the derived solutions is shown in Tables 2 and 3. It becomes clear that the hydropower production (MAEP) is not very sensitive to deviations from projected inflow and demand. A wrong assumption for future reservoir inflow and demand patterns would in the worst case result in 2.4% less energy production (which occurs when the Pareto-optimal rule set of scenario M2 is applied to scenario L). Interestingly, in many cases the overall energy production of cross-tested rule sets is higher than the applicable Pareto-optimal set. In each of these cases, the high energy production goes hand in hand with more severe water shortages (higher mean SI), indicating that these rules force releasing of water that should actually be preserved for periods of drought. The largest observed increase in SI is 0.28 (occurring when the rulesets optimized to scenario M2 are applied to scenario H).
Yet, in all cases the cross-tested rulesets are still performing better than the conventional operating rules. Figure 4(a) illustrates the obtained results for scenario H.

The reason why the operating rules can be considered rather insensitive to the supply and demand projections may be due to the one part that all scenarios have in common: each combination of socio-economic developments and climate change results in a future trend of increasing water demand and decreasing water availability. The main difference between the scenarios is the specific magnitude of this trend.

In Table 4 it is shown that, when applying MOPSO to the same optimization problem, deviations from the Pareto-fronts found with NSGA-II are relatively small. The mean performance difference of the solution sets is between −0.8% and +1.0% for the MAEP and between −0.01 and +0.02 for the SI. However, in particular on the edges of the Pareto-fronts, there are larger differences in performance. MOPSO was able to discover somewhat better solutions on one edge of the Pareto-front for scenario L. The solutions on the Pareto-front edges of scenarios M1 and A both yield more energy production and lead to increasing water shortages. This shows that MOPSO found a more elongated front for these scenarios. NSGA-II performs slightly better for scenarios M2 and H. Figure 4(b) illustrates this for scenario H. The general observation that
in all scenarios both algorithms converge to approximately the same optimum raises confidence in their robustness for practical application to reservoir optimization problems.

**CONCLUSIONS**

For the investigated water stress scenarios, adapted operating rules on average reduce the SI of this reservoir system from 0.36 to 0.06 and increase the MAEP with 6.4% (compared to the projected future performance of conventional reservoir operation). Robustness of these results was evaluated by comparing the cross-scenario performance of all optimized rule sets and by comparing the results of one optimization technique (NSGA-II) with another (MOPSO). Operating rules that are optimized to a specific inflow and demand scenario are shown to deliver at most 2.4% less energy production when being applied in any other of the considered scenarios. Similarly for the SI, a maximum increase of 0.28 was observed. Yet, for any scenario the potential performance losses are much smaller than the initial performance gain that was achieved by changing from conventional to the proposed adapted operation. As the investigated scenarios represent a wide range of potential socio-economic developments and climate change projections, it can be stated that the adapted reservoir operating rules can be regarded as quite robust. This robustness is likely to be the result of the one aspect that all considered scenarios have in common: all combinations of likely socio-economic developments and climate change projections...
result in more future water stress compared to the past, with just the exact severity as distinctive difference.

Even though often mentioned in literature as a potential drawback, the optimization algorithms themselves prove to deliver robust and consistent results, with only minor differences in performance. NSGA-II and MOPSO both consistently lead to similar solutions, raising confidence that they indeed closely approximate the true global optimum as outcome.

REFERENCES


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