Response to Reviewer #2

Title: Improving multi-objective reservoir operation optimization with sensitivity-informed dimension reduction

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Dear Reviewer:

We greatly appreciate your comments and suggestions, which are valuable and very helpful for revising and improving our paper. The responses to the comments are listed below.

Comment 1: The term 'problem decomposition' introduced in the title of the article and throughout the text is somewhat misleading. This term commonly refers to approaches when a complex problem is 'decomposed' in a number of simpler problems that can be solved in an easier manner. The approach in this article is different because here the same optimization problem is being solved, just with reduced number of decision variables. My suggestion is to change this term both in the title and throughout the text into something like: "Improving………with sensitivity-informed reduction of problem size" (for the title).

Response:

We agree with the reviewer that the term "dimension reduction" is better for the paper. We have changed the term "problem decomposition" into the term "dimension reduction" throughout the revised manuscript including the title.

Comment 2: Section 1 'Introduction' does not present any reference to addressing optimization of ROS by algorithms that seek the optimal reservoir operation policy as trajectories through time (e.g. Dynamic

Programming, Stochastic Dynamic Programming and more recently Reinforcement learning and others). This is not the approach taken in the current article where MOEA algorithms are used that treat the rule curve values in time as individual decision variables (parameters). However some recognition of the existence of the other methods mentioned above is needed in the introduction. There are sufficient references in HESS as well as in numerous other journals regarding these approaches.

Response:

We agree with the reviewer, and have added the description of relevant algorithms that seek the optimal reservoir operation policy as trajectories through time (e.g. Dynamic Programming, Stochastic Dynamic Programming and more recently Reinforcement learning and others) as follows.

"In order to solve the ROS problem, there are different approaches, such as implicit stochastic optimization (ISO), explicit stochastic optimization (ESO), and parameter-simulation-optimization (PSO) (Celeste and Billib, 2009). ISO uses deterministic optimization, e.g., dynamic programming, to determine a set of optimal releases based on the current reservoir storage and equally likely inflow scenarios (Young, 1967; Karamouz and Houck, 1982; Castelletti et al., 2012; François et al., 2014). Instead the use of equally likely inflow scenarios, ESO incorporates inflow probability directly into the optimization process, including stochastic dynamic programming and Bayesian methods (Huang et al., 1991; Tejada-Guibert et al., 1995; Powell, 2007; Goor et al., 2010; Xu et al., 2014). However, many challenges remain in application of these two approaches due to their complexity and ability to conflicting objectives (Yeh, 1985; Simonovic, 1992; Wurbs, 1993; Teegavarapu and Simonovic, 2001; Labadie, 2004).

In a different way, PSO predefines a rule curve shape and then utilizes optimization algorithms to obtain the combination of rule curve parameters that provides the best reservoir operating performance under possible inflow scenarios or a long inflow series (Nalbantis and Koutsoyiannis, 1997; Oliveira and Loucks, 1997).

In this way, most stochastic aspects of the problem, including spatial and temporal correlations of unregulated inflows, are implicitly included, and reservoir rule curves could be derived directly with genetic algorithms and other direct search methods (Koutsoyiannis and Economou, 2003; Labadie, 2004). Because PSO reduces the curse of dimensionality problem in ISO and ESO, it is widely used in reservoir operation optimization (Chen, 2003; Chang et al., 2005; Momtahen and Dariane, 2007). In this study, the PSO-based approach is used to solve the ROS problem."

Comment 3: Some clarifications are needed regarding Equation (1) on page 3725 that introduces the general formulation of the objective functions. Specifically, the term Wi,j(x), which represents the sum of delivered water for water demand i in year j, needs to be clarified. My understanding is that during one optimization trial the rule curve values for the selected periods in one year are set and then the system is simulated for 40 years (1956-2006) using predicted demands of 2030. This simulation results in storage volumes that are sometimes below the rule curves, which are resulting in water shortages calculated as demand – actually delivered water. The question is the following: Is the water actually delivered in these periods calculated with the reduction factors (α1 and α2) discussed in the paragraph just above Equation (1) or not? If these are used – please elaborate how these reduction factors are introduced (are they constant or dependent on how far below is the actual reservoir storage volume below the rule curve(s)?).

Response:

Firstly, water supply operation rule curves represent the limited storage volume for water supply in each period of an operating year, which is divided into 24 time periods (with ten days as scheduling time step from April to September, and one month as scheduling time step in the remaining months). Decision variables are storage volumes at different time periods on the operation rule curves. To provide long-term operation guidelines for reservoir management to meet expected water demands for future planning years, the projected water demands and long-term historical inflow are used. The optimization objective for water supply operation rule curves is to minimize water shortages during the long-term historical period. Therefore, Equation (1) computes the water shortages in all historical years. The explanations of symbols have been updated in the revised manuscript.

Secondly, during the long-term simulation, when actual water storage is below the water supply rule curve, the water demand has to be rationed, i.e., applying the rationing factor. In general, a reservoir has more than one water supply targets, and the different water demands can have different reliability requirements and thus different levels of priority in practice. During drought, water demand with lower priority should be rationed first, the reduction degree ought to be larger and water-supply reliability ought to be smaller. Therefore, the operation rule curve for the water supply with the lower priority and larger reduction degree is located above the operation rule curve for the water supply with the higher priority and smaller reduction degree. In this paper, Fig. 1 shows water supply operation rule curves for agriculture and industry, where α_1 and α_2 are the reducing factors for industrial water demand and agricultural water demand, respectively.

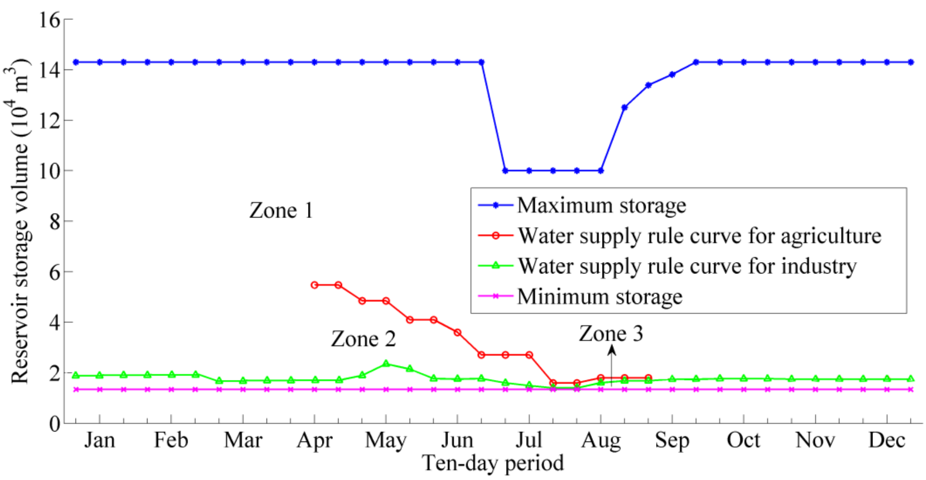

Fig. 1 Reservoir operational rule curves

Thirdly, the rationing factors used to determine the amount of water supply for different water demands can be either assigned according to the experts' knowledge or determined by optimization (Shih and ReVelle, 1995). In this paper, rationing factors are given at the reservoir's design stage according to the tolerable elastic range of each water user in which the damage caused by rationing water supply is limited. As mentioned above, rule curves for different water demands have different rationing factors, which remain constant and are not dependent on how far below is the actual reservoir storage volume below the rule curve during the long-term simulation. That is, as long as actual water storage is below the water supply rule curve, the water demand has to be rationed. Specifically, in Equation (1), the term $W_{i,j}(x)$ is the actually delivered water for water demand i during the jth year, and is calculated below using agricultural water demand $(i = 1)$ as an example. If the actual water storage is above the water supply rule curve for agricultural water demand $(i = 1)$ at period t in a year, the delivered water at period t is its full demand without being rationed, $D_{1,t}$. If the actual water storage is below the water supply rule curve for agricultural water demand at period t, the delivered water for agricultural water demand at period t is its rationed demands, $\alpha_1 * D_{1,t}$.

We have added the relevant clarifications in the revised manuscript.

Comment 4: Please provide some clarification regarding Figure 1. Is this just an example of rule curves for a reservoir (as suggested in the figure caption), or these are actual (currently used?) rule curves for Dahuofang reservoir (as suggested in the text on page 3723, lines 9-10)?

Response:

Fig. 1 is just an illustration of rule curves for Dahuofang reservoir based on the projected water demands and long-term historical inflow, and they are not actual (current used) rule curves. The currently used rule curves are in a similar shape but are based on the current water demands. This has been made clear in the revised manuscript.

Comment 5: If the rule curves in Figure 1 are actual for Dahuofang reservoir, the periods when there seem to be conflicting objectives (flood protection, agricultural water supply and industrial water supply) are limited (April-

October). Industrial water supply curve is very close to minimum storage throughout the year and agriculture water supply curve is considered only in the period April-October. The sensitivity–related results presented in Figure 4 are then not really clear. For example, how can the high sensitivity for industrial water supply curve in periods 1,2,3,10,11 and 12 (presumably January-March and October-December) be explained? Is this related to the interactive effects, only briefly mentioned in lines 22-24 on page 3730? The authors are kindly asked to provide clarifications / explanations regarding the sensitivity-related results presented in Figure 4.

Response:

As mentioned above, Fig. 1 is just an illustration of rule curves for Dahuofang reservoir based on the projected water demands and long-term historical inflow, and they are not actual (current used) rule curves.

The rule curves for Dahuofang reservoir from the final Pareto fronts based on the projected water demands and long-term historical inflow are shown in Fig. 8 (S2).

Firstly, the optimal operational rule curves in Fig. 8 (S2) have the same characteristics as they are used in practice. During the pre-flood season (from April to June), the curves gradually become lower so that they can reduce the probability of limiting water supply and empty the reservoir storage for the flood season (from July to early September). During the flood season, the curves also stay in low positions owing to the massive reservoir inflow and the requirement of flood control, so that it is beneficial to supply as much water as possible. However, during the season from mid-September to March, the curves remain high, especially from mid-September to October, in order to increase the probability of limiting water supply and retaining enough water for later periods to avoid severe water-supply shortages as drought occurs.

Secondly, Fig. 8 (S2) shows that different water demands occur at different periods, e.g., industrial water demand occurs throughout the whole year, and agricultural water demand occurs only at the periods from the second ten-day of April to the first ten-day of September. Due to the higher priority of industrial water supply than agricultural water supply, the industrial water supply curve is more close to minimum storage throughout the year than the agricultural water supply curve. Due to the conflicting relationship between industrial and agricultural water demands, the industrial water supply curve is higher during the non-flood season. Thus, if the industrial water supply curve is too low during the non-flood season from January to April, which implies that the industrial water demand is satisfied sufficiently, there would not be enough water supplied for the agricultural water demand in the same year. Similarly, if the industrial water supply curve is too low during the non-flood season from September to December, there would not be enough water supplied for the agricultural water demand in the next one or more years.

Thirdly, the inflow and industrial water demands are relatively stable during the non-flood seasons from January to March and from October to December, so one month is taken as the scheduling time step, which is in accordance with the requirement of Dahuofang reservoir operation in practice. Due to the larger amount of industrial water demand in periods 1, 2, 3, 10, 11 and 12 (January-March and October-December) than other periods, the water storages at these time periods are very important to industrial water supply, making them the most sensitive variables. Because the agricultural water demand is very high during the non-flood period from April to May, the agricultural water supply curve at this time period is higher, and the water storages at time periods from agr4-2 to agr5-3, i.e., the water storages at the first five time periods of water supply operation rule curve for agricultural water demand, are the most important variables. On the other hand, in practice, if the agricultural water demand could not be satisfied at the first few periods of water supply operation rule curve, the agricultural water supply at each period throughout the year would be limited, i.e., the interactive effects from variables are noticeable at time periods from agr4-2 to agr5-3.

We have added the above figure and more clarifications and explanations in the revised manuscript.

Comment 6: From Figure 1 it can be noticed that the second half of the period when water from the Dahuofang reservoir is needed for agriculture (irrigation) coincides with the flood season (therefore the conflict, since the reservoir storage needs to be reduced to accommodate the flood wave). This is also confirmed in the text on page 3728 (lines 17-19), when the decision variables for the agriculture water supply curve have been selected for the period April-September. However this is somewhat counter-intuitive. Why would irrigation be needed during the flood (wet) season? Can you please clarify this?

Response:

During the flood season, there are still agricultural water demands due to temporal and spatial variations of rainfall though they are significantly reduced. Also note that the water supply curves are developed based on a historical, long-term rainfall series and the projected demands are also based on historical demands, covering stochastic uncertainties in demands and rainfalls.

We have added some clarifications in the revised manuscript.

Comment 7: It is not clear how are the rule curve values set for periods that are not varied during the optimization (not considered as decision variables) in the simplified problems that also provide initial values for the pre-conditioned optimization. Please explain this somewhere in the article.

Response:

In this paper, the simplified problem is solved with the optimization of sensitive decision variables; and the insensitive decision variables are set randomly first with domain knowledge and kept constant during the solution of the simplified problem. Therefore, the solutions from the simplified problem, including optimal sensitive decision variables and the constant insensitive decision variables, are used as staring points for a complete new search.

We have added the relevant explanations in the revised manuscript.

Comment 8: Even though the article is largely focused on demonstrating the efficiency gains due to the introduction of the sensitivity analysis step, it will be good to show some results in terms of actual gains regarding the considered objectives after the optimization. Is there a base case (without optimization) to which optimal solutions can be compared? If yes, it will be good to show the shortages for the base case compared with few solutions from the final Pareto front(s) (e.g. one favoring industry, one favoring agriculture and one compromise solution), and to show in an additional figure the actual optimal rule curves for such solutions (to be compared perhaps with those in Figure 1).

Response:

As mentioned above, the currently used rule curves for Dahuofang reservoir are based on the current water demands. However, this paper aims to provide long-term operation guidelines for reservoir management to meet expected water demands for future planning years based on the projected water demands and long-term historical inflow. Therefore, comparisons are made among the optimized solutions from the final Pareto fronts, including industry-favoring solution (S0), agriculture-favoring solution (S1) and compromised solution (S2). The comparisons of water shortage indices among different solutions are shown in Table 3, and the optimal rule curves for different solutions are shown in Fig. 8.

Table 3 Comparisons of water shortage indices among different solutions

Solutions	Water Shortage Index (-)	
	Industrial water demand	Agricultural water demand
(S0) Industry-favoring solution	0.000	3.550
(S1) Agriculture-favoring solution	0.020	1.380
(S2) Compromised solution	0.007	1.932

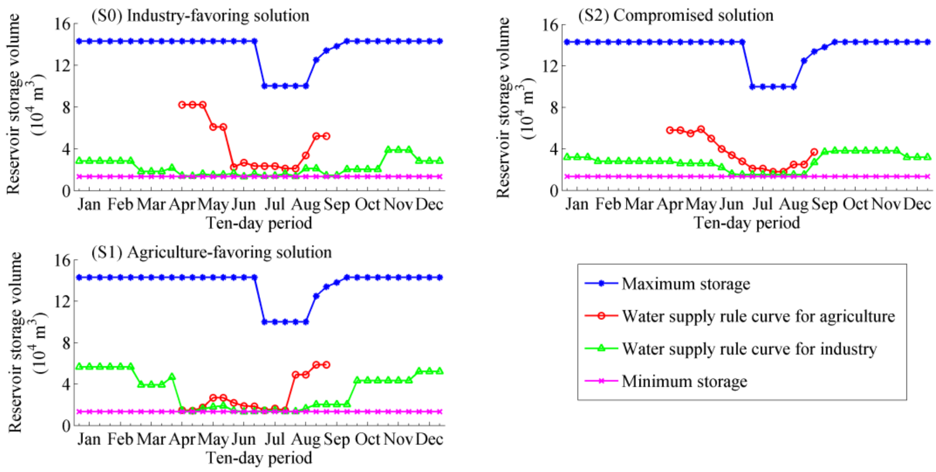

Fig. 8 Optimal rule curves for different solutions, (S0) Industry-favoring solution; (S1) Agriculture-favoring solution; (S2) Compromised solution

It could be seen from Table 3 and Fig. 8 that there are larger differences among different solutions. With industry-favoring solution (S0), the agricultural water supply curve at the period from April to May is the highest among the three solutions. Because the agricultural water demand is very high during the non-flood period from April to May, the highest position of agricultural water supply curve at these periods could cause that the agricultural water demand would not be satisfied at the first few periods of agricultural water supply operation rule curve, and the agricultural water supply at each period throughout the year would be limited easily. Therefore, in S0, the industrial water demand could be fully satisfied through limiting agricultural water supply to a large extend, and lowering the industrial water supply curve; industrial and agricultural water shortage indices are 0.000 and 3.550, respectively. Opposite to S0, the agricultural water demand in S1 could be satisfied largely through lowering the agricultural water supply curve on the period from April to May and raising the industrial water supply curve; and industrial and agricultural water shortage indices are 0.020 and 1.380, respectively. Compared with solutions S0 and S1, two objectives are balanced in compromised solution (S2), where industrial and agricultural water shortage indices are 0.007 and 1.932, respectively.

We have added the relevant explanations in the revised manuscript.

Comment 9: It will be good if the authors can provide in section 5.3 'Discussions'

some thoughts regarding the expectations for similar efficiency gains in other ROS optimization problems (and other water-related optimization problems in general). In other words, how much are the large efficiency gains reported case-specific (type of problem and problem formulation, selection of initial number of decision variables, etc) compared to gains that can be expected in general.

Response:

This study investigates the effectiveness of a sensitivity-informed optimization method for the ROS multi-objective optimization problems. The method uses a global sensitivity analysis method to screen out insensitive decision variables and thus forms simplified problems with a significantly reduced number of decision variables. The simplified problems dramatically reduce the computational demands required to attain Pareto approximate solutions, which themselves can then be used to pre-condition and solve the original (i.e., full) optimization problem.

In reality for a very large and computationally intensive problem, the full search with all the decision variables would likely be so difficult that it may not be optimized sufficiently. However, as shown here, these simplified problems can be used to generate high quality pre-conditioning solutions and thus dramatically improve the computational tractability of complex problems. The framework could be used for solving the complex optimization problems with a large number of decision variables.

For example, Fu et al. (2012) has used the framework for reducing the complexity of the multi-objective optimization problems in water distribution system (WDS), and applied it to two case studies with different levels of complexity - the New York Tunnels rehabilitation problem and the Anytown rehabilitation/redesign problem. For the New York Tunnels network, because the original optimization problem has 21 decision variables (pipes) and each variable has 16 options, the decision space is $16^{21} = 1.934 \times 10^{25}$. The simplified problem with 8 decision variables based on Sobol''s analysis have a decision space of $16^{8} = 4.295 \times 10^{9}$. To obtain the same threshold of hypervolume value 0.78 for the New York Tunnels rehabilitation problem, the most the pre-conditioned search need is 60 to 70% fewer NFE relative to the full search through 50 random seed trials. In the case of the Anytown network, the original problem has a space of 2.859×10^{73}, and the simplified problem has a significantly reduced space of 8.364×10^{38}. Through 50 random seed trials for the Anytown rehabilitation/redesign problem, the full search requires average of 800000 evaluations to reach hypervolume value 0.77, and the pre-conditioned search exceeds hypervolume value 0.8 in all trials in fewer than 200000 evaluations. The results also show that searching in such significantly reduced space formed by sensitive decision variables makes it much easier to reach good solutions, and the sensitivity-informed reduction of problem size and pre-conditioning improve the efficiency, reliability and effectiveness of the multi-objective evolutionary optimization.

We have added the relevant explanations in the revised manuscript.

Comment 10: Line 4 - page 3722 : Change 'neuron' to 'neural'.

Response:

We have changed 'neuron' to 'neural' in the revised manuscript.

Comment 11: Line 1 - page 3727: Change 'Since MOEA search is stochastic...' to 'Since MOAE uses random-based search…'

Response:

We have re-phrased the sentence to "Since MOEA uses random-based search…" in the revised manuscript.

Comment 12: Line 26 – page 3731: I don't understand the term 'diminishing returns' here. Perhaps it can be changed to 'diminishing values'?

Response:

We have changed 'diminishing returns' to 'diminishing values' in the revised manuscript.

Comment 13: When using the numbers for storage volumes or catchment areas in the presented cases, I would suggest to use values expressed as 10^3 or 10^6, etc (thousands, millions, etc) rather than other expressions like 10^5 or 10^8. I think it is easier for readers to get quickly the impression about the actual sizes.

Response:

The expressions have been changed in the revised manuscript.

References

Castelletti, A., Pianosi, F., Quach, X., Soncini-Sessa, R. 2012. Assessing water reservoirs management and development in Northern Vietnam. Hydrology and Earth System Sciences 16, 189-199.

Celeste, A.B., Billib, M. 2009. Evaluation of stochastic reservoir operation optimization models. Advances in Water Resources 32, 1429-1443.

Chang, F.J., Chen, L., Chang, L.C. 2005. Optimizing the reservoir operating rule curves by genetic algorithms. Hydrological Processes 19 (11), 2277-2289.

Chen, L. 2003. Real coded genetic algorithm optimization of long term reservoir operation. Journal of the American Water Resources Association 39 (5), 1157-1165.

François, B., Hingray, B., Hendrickx, F., Creutin, J.D. 2014. Seasonal patterns of water storage as signatures of the climatological equilibrium between resource and demand. Hydrology and Earth System Sciences 18, 3787-3800.

Fu, G.T., Kapelan, Z., Reed, P. 2012. Reducing the complexity of multi-objective water distribution system optimization through global sensitivity analysis. Journal of Water Resources Planning and Management 138 (3), 196-207.

Goor, Q., Halleux, C., Mohamed, Y., Tilmant, A. 2010. Optimal operation of a multipurpose multireservoir system in the Eastern Nile River Basin. Hydrology and Earth System Sciences 14, 1895-1908.

Huang, W.C., Harboe, R., Bogardi, J.J. 1991. Testing stochastic dynamic programming models conditioned on observed or forecasted inflows. Journal of Water Resources Planning and Management 117, 28-36.

Karamouz, M., Houck, M.H. 1982. Annual and monthly reservoir operating rules generated by deterministic optimization. Water Resources Research 18 (5), 1337-1344.

Koutsoyiannis, D., Economou, A. 2003. Evaluation of the parameterization-simulation-optimization approach for the control of reservoir systems. Water Resources Research 39 (6), WES2.1-WES2.17.

Momtahen, S., Dariane, A.B. 2007. Direct search approaches using genetic algorithms for optimization of water reservoir operating policies. Journal of Water Resources Planning and Management 133 (3), 202-209.

Nalbantis, I., Koutsoyiannis, D. 1997. A parametric rule for planning and management of multiple-reservoir systems. Water Resources Research 33 (9), 2165-2177.

Oliveira, R., Loucks, D.P. 1997. Operating rules for multireservoir systems. Water Resources Research 33 (4), 839-852.

Powell, W.B. 2007. Approximate Dynamic Programming: Solving the Curses of Dimensionality. John Wiley & Sons, Inc., ISBN-13: 9780470171554.

Shih, J.S., ReVelle, C. 1995. Water supply operations during drought: a discrete hedging rule. European Journal of Operational Research 82 (1), 163-175.

Simonovic, S.P. 1992. Reservoir systems analysis: closing gap between theory and practice. Journal of Water Resources Planning and Management 118 (3), 262-280.

Teegavarapu, R.S.V., Simonovic, S.P. 2001. Optimal operation of water resource systems: trade-offs between modeling and practical solutions. In: Mariño, M.A., Simonovic, S.P., editors. Integrated water resources management 272 (IAHS Publ), 257-263.

Tejada-Guibert, J.A., Johnson, S.A., Stedinger, J.R. 1995. The value of hydrologic information in stochastic dynamic programming models of a multireservoir system. Water Resources Research 31, 2571-2579.

Wurbs, R.A. 1993. Reservoir-system simulation and optimization models. Journal of Water Resources Planning and Management 119 (4), 455-472.

Xu, W., Zhang, C., Peng, Y., Fu, G.T., Zhou, H.C. 2014. A two stage Bayesian stochastic optimisation model for cascaded hydropower systems considering varying uncertainty of flow forecasts. Water Resources Research 50, doi:10.1002/2013WR015181.

Yeh, W.W.-G. 1985. Reservoir management and operations models: a state-of-the-art review. Water Resources Research 21 (12), 1797-1818.

Young, G.K. 1967. Finding, reservoir operating rules. Journal of Hydraulic Division 93 (HY6), 297-321.