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Improving the future performance and reliability of multi-reservoir systems by multi-objective optimization

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Abstract Current climate circulation models simulate a climate change-induced decreasing amount of precipitation in the region of Saxony (Germany) in summer. Consequently, the operation of reservoirs has to consider decreasing inflows, more severe drought periods, as well as increasing demands for water. In order to adapt to these new pressuring conditions and to meet the future demands of all water sectors and simultaneously to provide flood protection, new management strategies for the reservoirs are required. This study combines multi-objective optimization and Monte Carlo simulation for finding effective management strategies for multi-purpose multi-reservoir systems. To achieve robust operations, a new framework is developed which comprises: (i) the physically-based rainfall–runoff model, (ii) a time series model for the generation of a large number of synthetic inflow time series, (iii) a comprehensive reservoir model, and (iv) an adapted multi-objective optimization algorithm and advanced visualization methods for a compact presentation of the results for the decision maker. In a real case application, the new framework is used to find operating rules of a multi-purpose multi-reservoir system in the Ore Mountains, Germany. The overall robustness of the multi-reservoir system operation is quantified and trade-offs between management goals and reservoir utilizations are shown.

Key words multi-purpose multi-reservoir system; multi-objective optimization; rule curves; visualization

INTRODUCTION

According to climate-change projections, the central and eastern regions of East Germany could particularly suffer from dry summers (Franke *et al.*, 2004). For mitigation, new control policies are needed for the reservoir systems in the region of Saxony for climate change adaptation. For a quantitative assessment of vulnerability of a reservoir system to climate change, commonly large-scale atmospheric variables predicted by general circulation models (GCMs) are used to downscale to basin-scale hydrologic variables, through statistical relationships or using a regional climate model (Raje & Majumdar, 2010). Typically, ensembles of GCMs are used as inputs for hydrological models, which then generate the resulting inflows into the reservoir system. However, the resulting scenario ensembles mostly have a limited number of realizations which prevents a meaningful statistical analysis and reliability analysis of future reservoir operation.

In the case of multiple, often contradicting management goals, multi-objective analysis is a powerful tool for the determination of effective operating strategies of a reservoir system. Multi-objective optimization (MOO) is an increasingly popular method in optimal reservoir operation (Reddy & Kumar, 2006; Chen *et al.*, 2007; Kim *et al.*, 2008; Chang & Chang, 2009; Dittmann *et al.*, 2009). Multi-objective evolutionary techniques are commonly applied in these studies and mostly a large number of Pareto optimal solutions are provided to the decision-maker as the result. But for them it may be hard to analyse large sets of possible solutions, especially if more than two objectives are involved. Considering these two limitations a new framework for multi-objective optimization and analysis (MOO framework) is proposed, which is based on physically-based modelling, an extended time series model for the generation of a long inflow time series, an adapted MOO algorithm, and advanced visualization methods for a compact presentation of the results for the decision maker.

METHODS

The general strategy for finding effective and robust management strategies for multi-purpose reservoirs and multi-reservoir systems combines multi-objective optimization and Monte Carlo simulation. In this study a framework with a sequential procedure is proposed. As can be seen from Fig. 1 the MOO framework can be used in two modes, the assessment of recent conditions

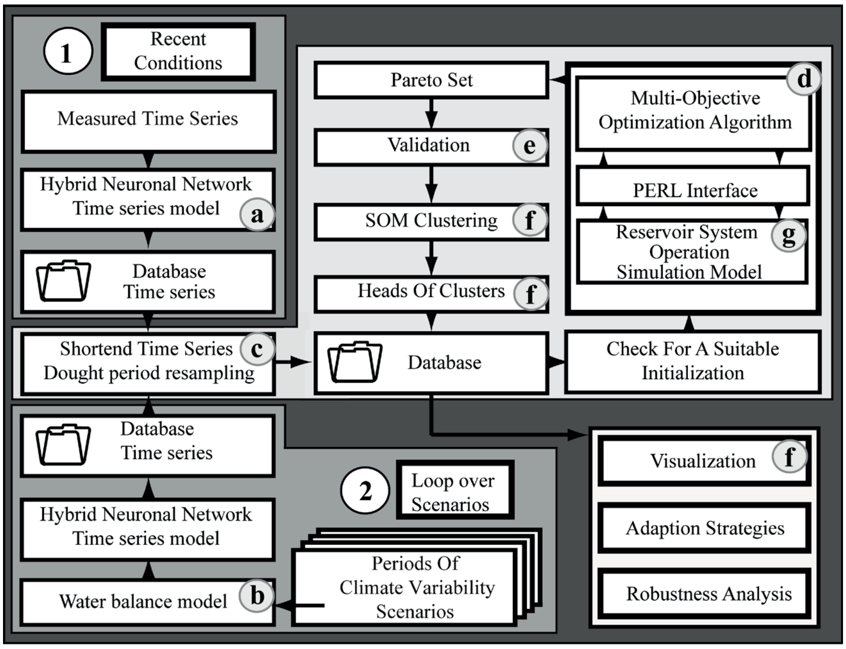

Fig. 1 Flow chart of the multi-objective optimization framework. Upper part (1): For recent climatic conditions the database is measured data. Lower part (2): For climate change scenarios a water balance model is used to generate the inflow databases.

using observed inflow data (see upper figure) and the assessment of climate change impacts using a hydrological model (see lower figure). The single steps of the MOO framework are as follows.

Modelling monthly reservoir inflows for climate change scenarios

For the assessment of future climate conditions, inflows are modelled on a daily time step using the distributed physically-based deterministic water balance model WaSiM-ETH (Schulla, 1997), see Fig. 1, box (b). Meteorological data is provided by given climate change scenarios which are predicted by a combination of general circulation models (GCMs) and a regional climate model.

Stochastic generation of long time series

For generating a large inflow time series on the basis of observed inflow data and/or simulated data by rainfall–runoff modelling, a multivariate time series model is used which is able to simulate all inflows in the reservoir model (Fig. 2) simultaneously (see Fig. 1, box (a)). The time series model is based on a hybrid artificial neuronal network (HANN; Ashrafzadeh & Rizi, 2009). A combination of a k-nearest neighbourhood technique together with an artificial neuronal network allows the prediction of new, potentially correlated reservoir inflows. The HANN time series model used here is extended with a moving average filter (Langousis & Koutsoyiannis, 2006) to account for long-term persistence.

Resampling of long time series

A combined MOO and Monte Carlo simulation of a multi-reservoir system with a simulation period of, for example, 10 000 years, is computationally very costly. Using a Monte Carlo resampling technique, a significant shorter time series can be constructed which maintains the statistical characteristics and the empirical distribution function of deficit volumes. The procedure of the resampling scheme (see Fig. 1, box (c)) is as follows: first, a sequence peak algorithm is used to separate drought periods and their respective deficit volumes in the original time series. Second, using the normal-quantile transformation, the deficit volumes are transformed to follow a standard normal distribution. Third, the empirical cumulative distribution (ECD) of the set of transformed deficit volumes and a set of uniformly distributed random numbers is used to sample deficit volumes randomly. The ECD of the sampled set of deficit volumes is constructed and the Pearson correlation coefficient ρ between the two sets for values with an exceedence frequency $p_e \geq 0.9$ is calculated. The third step is repeated until a set of deficit volumes is sampled so that $\rho \geq 0.995$ .In the last step the sampled drought periods are rearranged to build a legitimate time series. Drought periods from the set are attached successively to the time series so that ending and starting months of the periods are legitimate. When no more periods with legitimate starting months can be found, all remaining periods in the set are extended to begin with the first month of the year and end with the last month of the year. Then the attaching process is continued.

Reservoir system operation model

The reservoir system is modelled using the generalized reservoir system operation model OASIS (see Fig. 1, box (g)). OASIS (Hydrologics Inc., 2009) is a mixed integer linear programming solver model which is used to simulate a period of record by optimizing the operations for a single time step. This can be seen as a short-term optimization. Constraints that are given by, e.g. minimum and maximum flows, maximum storage volumes, which are all handled by the OASIS model or by an interface implemented in the programming language PERL which couples the OASIS model with the global, long term optimization model MO-CMA-ES (see below).

Generalized multi-objective optimization framework

For multi-objective optimization of the multi-reservoir system the multi-objective evolutionary strategy MO-CMA-ES (Igel *et al.*, 2007) is combined with the generalized reservoir system operation model OASIS (see Fig. 1, box (d)). A box constraint handler as described in Igel *et al.* (2007) is used and the algorithm was extended to handle eight simulation model runs in parallel using the OpenMP (OpenMP Architecture Review Board 2002) framework. Communication and evaluation of the objective function is realized by a PERL interface. All Pareto-optimal solutions that are obtained by the MOO are validated against the long original time series (see Fig. 1, box (e)). To ensure a high robustness of the solutions presented to the decision maker, only solutions passing the required restrictions, e.g. the minimum reliability of supply, as kept in the set of Pareto-optimal solutions. All other solutions are discarded.

Advanced visualization technique for multi-objective decision analysis

Mostly a large number of Pareto optimal solutions are provided by MOO to the decision maker and he has to analyse the trade-off between objectives and to select the most preferable solution among hundreds of solutions, according to his preferences. Appropriate visualization techniques which aim to simplify complex Pareto sets without sacrificing completeness of the solution space have been developed in recent years. In this study, level diagrams (Blasco *et al.* 2008) and extensive clustering of the solutions in the Pareto set are employed to get inside the salient features of n-dimensional Pareto fronts (see Fig. 1, box (f)). With Level Diagrams the solutions of the Pareto Front are classified according to their distance to the utopia point by normalizing each of the objective functions F_i, $i = 1, \ldots, s$, of the vector of objective functions $\mathbf{F} = [F_1, \ldots F_s]$ by $\overline{F_i} = (F_i - \widetilde{F_i})/(\hat{F_i} - \widetilde{F})$, where $\hat{F_i} = \max(F_i)$ and $\widetilde{F} = \min(F_i)$; then the distance to the utopia point can be obtained by choosing a suitable norm like the 1-norm (Manhattan norm) with $\|F\|_1 = \sum_{i=1}^{s} |\overline{F}|$. In the visualization step the objective function value of each solution on the abscissa is plotted against its computed distance to the utopia point on the ordinate in an own representation for each objective function. Therefore a solution has the same position on the ordinate in every representation, which makes the plot easily comprehensible. With the 1-norm solutions near the utopia point, which means low ordinate values in the Level diagrams, give good compromises between all objectives. Deviating from Zio & Bazzo (2011), a clustering technique based on self organizing maps (SOM; Kohonen, 2001) is used for the clustering of the Pareto set by a weighted combination of the objective space $\overline{F}_i$, the normalized decision space θ and the 1-norm $\|\mathbf{F}\|_1$ of the Pareto Front. The representative solution is chosen for each cluster to have the minimum mean 1-norm to all other solutions in the cluster. The alpha shape algorithm (Edelsbrunner *et al.*, 1983) is utilized in the visualization step to draw the concave hull of all solutions in the cluster into the Level Diagram together with the representative solution.

CASE STUDY

To demonstrate the working of the proposed MOO framework, it is used in a first step to find optimal operating strategies for the recent climatic conditions for the multi-purpose multi-reservoir system Klingenberg-Lehnmühle-Rauschenbach in the Ore Mountains (Saxony, Germany), referred to as the KB-LM-RB system. The KB-LM-RB system (see Fig. 2) consists of two reservoirs (Klingenberg and Lehnmühle in the catchment of the River Weißeritz) in series, with an additional diversion from a third reservoir (Rauschenbach in the catchment of the River Flöha).The reservoir system was built for the purpose of flood protection and water supply for domestic and industrial use, mainly for the towns of Dresden and Freital.

Table 1 Reservoirs in the KB-LM-RB reservoir system.

Reservoir	z_0 (hm^3)	z_1 (hm^3)	Q_I (hm^{3}per year)
Lehnmühle	2.5	14.91	34.7
Klingenberg	2.0	14.31	45.7*
Rauschenbach	2.3	11.20	16.6

z_0 : buffer zone; z_1 : conservation zone; Q_I : Total inflow per year. * Including the inflow from reservoir Lehnmühle.

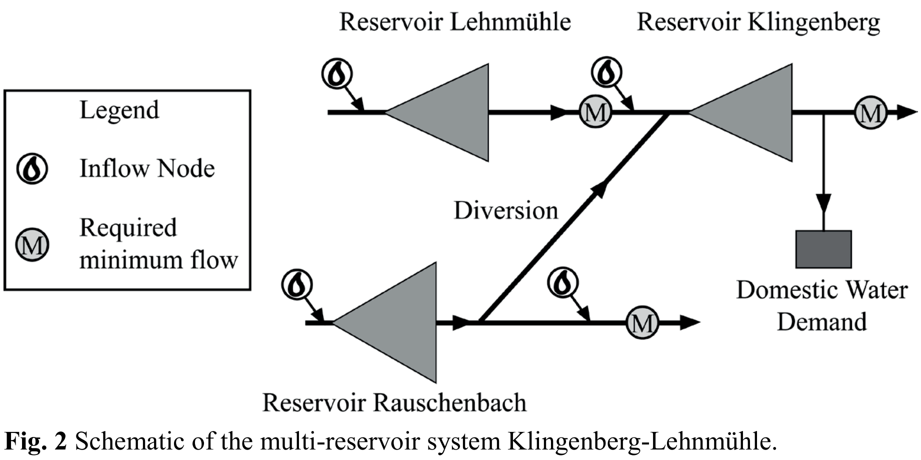

Fig. 2 Schematic of the multi-reservoir system Klingenberg-Lehnmühle.

For the KB-LM-RB system a data set of monthly inflows over 89 years (1921–2010) is available. Using the HANN time series model 10 000 years of monthly multivariate inflow time series were generated. By utilizing the resampling method a shorter time series of 635 years of monthly multivariate data was then created for the simulation of the KB-LM-RB reservoir system in the MOO step.

Mathematical model formulation

The three objective functions of the global MOO problem are designed to reflect the different main reservoir utilizations and management goals of the KB-LM-RB system.

Objective function F_1, equation (1), maximizes the overall reliability of domestic water supply. Since minimum reliabilities of supplies are necessary for the three different levels of supply LS_l, $l = 1,...,3$ the objective space of the MOO is restricted by constraints, e.g. by heavily penalizing solutions with unsatisfactory reliabilities of supplies, see equations (1.1) to (1.3) and equation (4).

$$\min(F_1) = \min\left(f_{F1,1} + f_{F1,2} + f_{F1,3} + f_{F1-3}\right) \tag{1}$$

$$f_{F1,1} = \begin{cases} -1 \times \left(\dfrac{p_1 - \lambda_1}{1 - \lambda_1} \right) & if \quad p_1 \geq \lambda_1 \\ 1 - \dfrac{p_1}{\lambda_1} & otherwise \end{cases} \tag{1.1}$$

$$f_{F1,2} = \begin{cases} -1 \times \left(\dfrac{p_2 - \lambda_2}{1 - \lambda_2} \right) & if \quad p_2 \geq \lambda_2 \\ 1 - \dfrac{p_2}{\lambda_2} & otherwise \end{cases} \tag{1.2}$$

$$f_{F1,3} = \begin{cases} -1 \times \left(\dfrac{p_1 - \lambda_3}{1 - \lambda_3} \right) & if \quad p_3 \geq \lambda_3 \\ 1 - \dfrac{p_3}{\lambda_3} & otherwise \end{cases} \tag{1.3}$$

$p_l = p(Q_D \geq Q_l)$ is the exceedence probability of the amount of delivered domestic water Q_D being greater or equal to the required demand Q_l at level of supply LS_l. Q_D is the amount of actual delivered domestic water. λ_l is the required exceedence probability or reliability of supply for the supply of domestic water at LS_l from the reservoir Klingenberg.

Objective F_2, equation (2), maximizes the exceedance probability of a filled reservoir Klingenberg in the month of April. F_2 serves as a proxy variable for water quality.

$$\min(F_2) = \min\left(-1 \times \left(p(S_{KL} \geq V_{KL}) + f_{F1-3}\right)\right) \tag{2}$$

Objective Function F_3 minimizes the amount of diversion from reservoir Rauschenbach, which is a basic management goal, in order to minimize the costs for pumping. This is given in equation (3) where $Q_{Div,t}$ is the diverted water at the time step t of a total of T time steps in the simulation. A management goal in the reservoir system is to keep the amount of diversions as small as possible. Therefore, the mean monthly amount of diverted water from reservoir Rauschenbach is minimized in objective function F_3.

$$\min(F_3) = \min\left(\sum_{t=1}^{T} Q_{Div,t} + f_{F1-3} \right) \tag{3}$$

Objective functions F_1, F_2 and F_3 contain a penalty term, equation (4) that is triggered if the required reliability of supply levels are not met.

$$f_{F1-3} = \begin{cases} 10E6 & if \ \exists\left(p_1 < \lambda_1 \wedge p_2 < \lambda_2 \wedge p_3 < \lambda_3\right) \\ 0 & otherwise \end{cases} \tag{4}$$

The MOO of the multi-reservoir system requires adopting four rule curves, represented by the $\mathbf{Z}$ including 12 storage values each for the months of the year, resulting in a MOO problem with 48 decision variables. All rule curves relate their specific subject of management to the accumulated current storage S_i^{total} of the reservoirs Klingenberg and Lehnmühle, $S_i^{total} = S_i^{KL} + S_i^{LM}$ .The first pair of rule curves $\mathbf{Z}^{KL,1}$ and $\mathbf{Z}^{KL,2}$ separates the three zones of levels of supply in the conservation zone of reservoir Klingenberg. LS_1 and LS_2 are separated by the upper $\mathbf{Z}^{KL,1}$ and LS_3 is separated from LS_2 by the lower $\mathbf{Z}^{KL,2}$. Each level of supply has its own level of security of supply and its own demand, see Table 2. The last pair of rule curves regulates the diversion of water from reservoir Rauschenbach to reservoir Klingenberg (see Fig. 2). The upper rule curve $\mathbf{Z}^{Div,1}$ separates a zone with no diversion from the first diversion zone with 0.4 hm^3/month. The lower rule curve $\mathbf{Z}^{Div,2}$ separates the first diversion zone and the second diversion zone with a diversion rate of 0.6 hm^3/month. The layering in of the rule curves in the conservation zone necessitates the constraints $z_0^{KL} + z_0^{LM} \le \mathbf{Z}^{KL,1} \le \mathbf{Z}^{KL,2} \le z_1^{KL} + z_1^{LM}$ and $0 \le \mathbf{Z}^{Div,1} \le \mathbf{Z}^{Div,2} \le z_1^{KL} + z_1^{LM}$ for the levels of supply and the diversion of water from Rauschenbach.

Table 2 Table of levels of supplies for Reservoir Klingenberg(* used as threshold for MOO).

Level of supply	$LS_{l=1}$	$LS_{l=2}$	$LS_{l=3}$
Demand Q_l (m^{3}s^{-1})	1.00	0.925	0.85
Reliability of supply $\lambda_{o,j}$ (%)	99	99.5	99.95
Reliability of supply* λ_l (%)	98	99	99.7

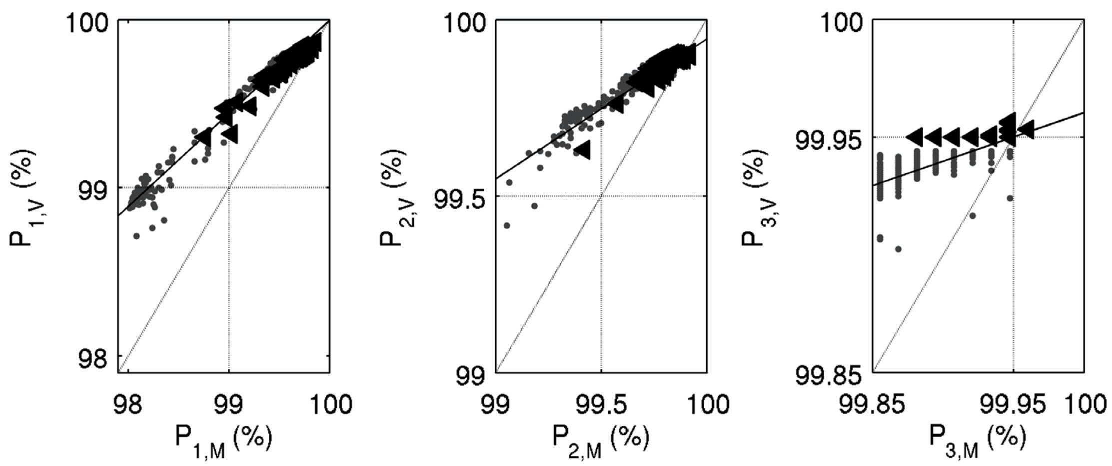

Fig. 3 From left to right: reliabilities of supplies for the different levels of supply for all Pareto-optimal solutions as obtained in the MOO $p_{l,m}$ and as simulated in the validation $p_{l,V}$. Robust solutions are black. The black solid line shows the linear fit between $p_{l,m}$ and $p_{l,V}$ values.

RESULTS

Validation of the Pareto optimal solutions for the resampled time series

The MOO framework applied to the KB-LM-RB system provided 605 Pareto optimal solutions after 192 000 model evaluations using a MO-CMA-ES population of 48 parents and 48 offspring. After the validation of all Pareto optimal solutions yielded in the MOO, on the basis of the resampled time series of 635 years, a set of still 98 solutions remained in the final solution set which is consistent with the original time series of 10 000 years. Figure 3 shows the results of the validation providing the insight for assessing the error which is caused by the resampling. For a detailed analyses let $p_{l,M}, l = 1,...,3$ be the relaxed reliabilities of supply for the three levels of supply that is achieved by a solution in the MOO step (which allowed a more efficient optimization) and $p_{l,V}, l = 1,...,3$ the given reliabilities of supply in the validation step, respectively (see Table 2). As can be seen in Fig. 3 a significant number of validated Pareto optimal solutions (black diamond's) show reliabilities $p_{l,M}$ which are below the required reliabilities of supplies $\lambda_{o,l}$. The remaining 98 feasible solutions are indicated as black circles, which show that the validation analysis is imperative.

Clustering and visualization of Pareto optimal solutions for multi-objective decision analysis

The compact visualization of the objective functions values F_1 to F_3, as obtained for the feasible solutions in the validation, is shown in the Level Diagrams in Fig. 4. Note that each solution is located on the same ordinate level and can therefore easily be found on all objective function plots. Two clusters, Cl-1 and Cl-2, with two representative solutions, were identified using the SOM clustering method. The representative solution in a cluster is chosen to have highest similarity to all other solutions in the cluster that is the minimum mean Euclidean distance to all other solutions in the parameter space of the set of the considered cluster. All representative solutions are good compromise solutions since the distance to the utopia point is low for all the three objectives. As can be seen in Fig. 4, Cluster Cl-1 and Cl-2 cover two mostly separate regions for F_1 and F_2 while sharing a common region of high overall reliability of supply. Cluster Cl-1 is trading a high overall reliability of supply and a low amount of mean monthly diversion against a lower probability of a filled reservoir Klingenberg in the month of April. Cluster Cl-2 covers the whole range of F_1 indicating a high variability of rule curves in the cluster.

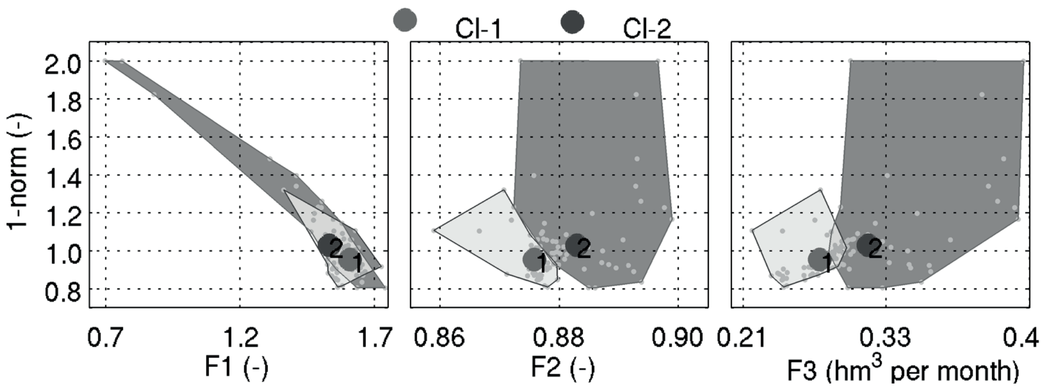

Fig. 4 Level Diagrams showing the results of the three objective functions F_1, F_2 and F_3 after validation. The grey areas mark the concave hull of all solutions belonging to the respective cluster. The numbered points are the representative solution for the cluster with the same colour.

An in-depth analysis of different sets of rule curves is shown in Fig. 5(a) for cluster set Cl-1 and Fig. 5(b) for cluster set Cl-2. In both figures, black lines show rule curves for representative solutions and the grey area covers the area of the 5% to 95% quantile range for the rule curve of the considered cluster set. Most rule curves show a significant seasonality and take the lower inflows in summer (except July) into account. For cluster Cl-1, Fig. 5(a) reveals that rule curves typically have a second peak in August in the supply level LS_1 and show lower diversions if enough water is stored in both reservoirs Klingenberg and Lehnmühle. In contrast, rule curves of cluster Cl-2 shown in Fig. 5(b) have a more balanced shape but lead to higher diversions throughout the year.

In summary, it can be seen that the decision maker can rely on the provided representative solutions of both clusters. In addition, the provided representative solutions show the main differences in the space of alternatives for the operation of the reservoir systems and the diversion. The grey dots show the solutions with the lowest distance to the utopia point.

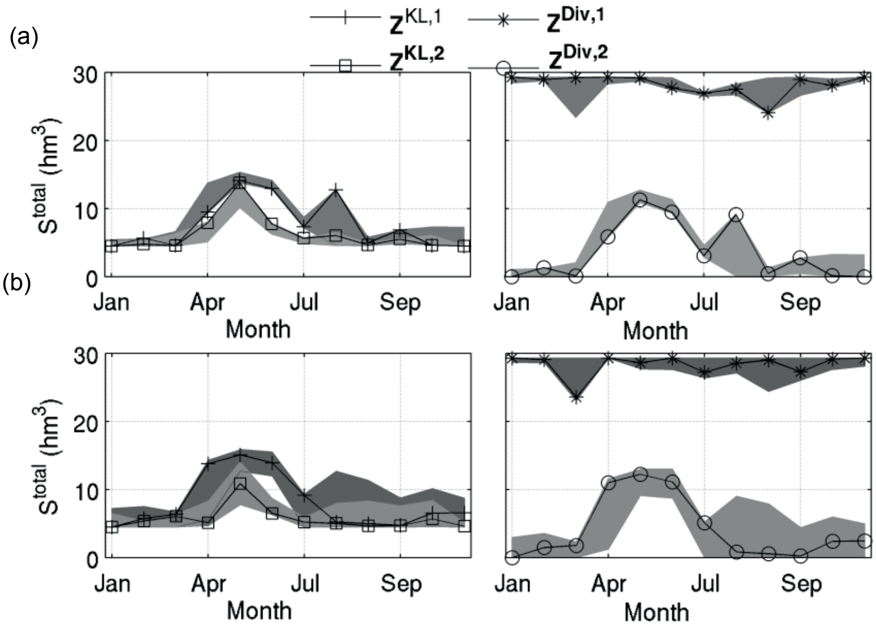

Fig. 5 Upper figures (a) show selected rule curves for Cluster Cl-1 and lower figures (b) for Cl-2. The black solid line marks the representative solution. Each grey area represents the quantile range from 5% to 95% for all solutions of one set of an optimized rule curve.

CONCLUSIONS

To achieve robust operating strategies for recent and future climate conditions a new framework is developed which combines Monte Carlo simulation and multi-objective optimization. The Monte Carlo simulation is based on a long time series of inflows, which allows for the evaluation of reservoir operation strategies to work with high quantiles (i.e. high reliabilities). An adapted resampling strategy makes the Monte Carlo simulation computationally more efficient since significantly fewer realizations are required.

In this study, novel clustering and visualization techniques are proposed which support the decision maker in the assessment and selection of the most preferable solution among hundreds of solutions according to his preferences. The application of so-called “Level Diagrams” provides a better and more comprehensive insight into the objective space and the set of Pareto optimal solutions than simple plots of the objective function space and/or its projections. Clustering of the high-dimensional parameter space helps the decision maker to deal with only a few representative solutions.

In a real case application, the MOO framework is used to find optimal operating strategies under recent climatic conditions for a multi-purpose multi-reservoir system. The multi-objective optimization yielded robust solutions for operation of the reservoir system with reliabilities of water supply of between 99 and 99.95%. Research is under progress using the MOO framework for finding operating strategies to potential impacts of the projected climate change. For this purpose a hydrological rainfall–runoff model is applied to different climatic conditions and different scenarios describing increased demands or enlarged flood protection zones are considered.

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