Exploring the relationships among reliability, resilience, vulnerability of water supply using many-objective analysis

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Abstract: Reliability, resilience and vulnerability are the most commonly used performance criteria for water supply planning and management. However, there is lack of understanding of the relationships among these criteria. This paper aims to reveal the relationships among them by using an emerging many-objective visual analytics. To measure different aspects of water supply systems in terms of reliability, resilience and vulnerability, a suite of five metrics are considered: water supply reliability, mean and maximum deficits of water supply as well as mean and maximum durations of water shortage. Results obtained in this study reveals that both conflicting and synergetic relationships exist between reliability and resilience (mean deficit of water supply), and between vulnerability (mean duration of water shortage) and resilience (mean deficit of water supply) in different regions of the objective space. A more complete picture of the relationships among reliability, resilience and vulnerability than reported in the prior literature is provided in this paper thanks to the use of many-objective analysis. This study provides an in-depth understanding of the relationships and can help decision makers make an informed decision in the management of water resources systems.

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1 Introduction

In a groundbreaking study by Hashimoto et al. (1982), the use of reliability, resilience and vulnerability as criteria was proposed for water resources planning and management. Since then these three performance criteria have been extensively applied to the analysis of water resources systems (e.g., Moy et al., 1986; Bayazit and Unal, 1990; Hsu, 1995; Vogel et al., 1995; Loucks, 1997; Srinivasan et al., 1999; Cai et al., 2002; Kjeldsen and Rosbjerg, 2004; Jain and Bhunya, 2008; Mondal et al., 2010; Sandoval-Solis et al., 2011; Fayaed et al., 2013; Chanda et al., 2014; Sağlam, 2015). In particular, in recent years, there has been increasing attention on the resilience of water systems, with a paradigm shift from 'fail – safe' (reliability) to 'safe to fail' (resilience) (Butler et al., 2016). As reliability, resilience and vulnerability describe different characteristics of a water system, there is a critical need to understand the relationships among the three criteria. In a real world, the selection of criteria in different water resources systems are largely based on experience. Hence, the relationship analysis is particularly important for the decision maker to understand how different criteria interplay and to make an informed decision on water system planning and management (Hashimoto et al., 1982).

There are few attempts to investigate the holistic relationships among the three criteria, though the relationships were discussed in prior studies (e.g., Hashimoto et al., 1982; Moy et al., 1986; Bayazit and Unal, 1990; Srinivasan et al., 1999). According to Hashimoto (1982) and Moy et al. (1986), there exists an obvious negative relationship (tradeoff) between reliability and vulnerability while reliability and resilience are positively related (synergy) under different operating rules in a water supply reservoir system. Bayazit and Unal (1990) reported a complex and nonlinear relationship between reliability and resilience. However, none of the above studies has provided a holistic relationship picture among the three criteria due to an incomplete set of optimal solutions used to explore the relationships or the optimization problem formulations used to obtain the solutions. For example, rather than using metrics to directly represent reliability, resilience and vulnerability in the optimisation process, Hashimoto et al. (1982), Bayazit and Unal (1990) used a single surrogate objective in the optimisation process, and a small number of optimal solutions were obtained by changing the value of a parameter in the surrogate objective and then they were re-evaluated regarding reliability, resilience and vulnerability for studying their relationships. Moy et al. (1986) and Srinivasan et al. (1999) used a single objective optimization method and obtained a small number of optimal solutions by swapping constraints with objectives. These methods could generate only a limited number of discrete points on the Pareto approximate frontier and provide an incomplete picture of the relationships.

The latest developments in many-objective optimization and visual analytics allow for a full exploration of the relationships among reliability, resilience and vulnerability. For example, the epsilon NGSA II (ε-NSGAII), amongst other popular algorithms, has been demonstrated to be able to obtain effectively a set of approximate Pareto-optimal solutions for many-objective optimization problems which have more than three objectives (Kollat and Reed, 2006; Kollat et al., 2011; Kasprzyk et al., 2012; Reed et al., 2013). Meanwhile, highly interactive visual analytics tools developed in recent years can assist the decision maker to explore the Pareto-optimal solutions in a more intuitive way (Kollat et al., 2011; Reed et al., 2013). These tools can be used as an effective way to explore the decision space and identify underlying relationships between the Pareto-optimal solutions (Kasprzyk et al., 2009; Fu et al., 2013).

This paper aims to reveal the full relationships among reliability, resilience, vulnerability of water supply in a reservoir system using many-objective optimization. Considering the different definitions of the three performance criteria, five metrics are formulated as optimization objectives to obtain optimal reservoir operating rules: (1) maximizing the reliability of system (α), (2) minimizing the mean duration of water shortage events ($\gamma_{\_mean}$), (3) minimizing the maximum duration of water shortage events ($\gamma_{\_max}$), (4) minimizing the mean severity of water shortage ($\nu_{\_mean}$), and (5) minimizing the maximum severity of water shortage ($\nu_{\_max}$). Then ε-NSGAII is used to solve the many-objective problem and the tradeoffs among the objectives are analyzed with a highly interactive visual tool. An optimal reservoir operation problem for the Biliu River Reservoir in northeast China is taken as a case study. The results show that the relationship among the three criteria is more complex than previously revealed.

2 The reservoir optimization problem formulation

To reveal the relationship among reliability, resilience and vulnerability of the water supply reservoir, the reservoir optimal operation problem is formulated as a many-objective optimization problem of five objectives. Although the reservoir optimal operation problems are generally designed via stochastic dynamic programming (SDP) (Labadie, 2004; Shokri et al., 2013; Xu et al., 2014), the problem in this paper is designed via the parameterization-simulation-optimization (PSO) approach (Celeste and Billib, 2009) , which is also called EMODPS and has been demonstrated to be especially effective for the many-objective problems by Giuliani et al. (2016). The PSO approach starts with the shape of the rule already established and defined by some few parameters (Celeste and Billib, 2009). In this paper, the shape of the reservoir operating rule curves references the hedging rule investigated by Shih and ReVelle (1994; 1995), Draper and Lund (2004). The formulations of the objectives, constrains, operating rules and the evolutionary optimization method of this optimal problem are introduced in detail below.

2.1 Objectives

There exist a number of definitions for reliability, resilience and vulnerability in previous studies. As different characteristics of water shortage events such as frequency, duration, and severity should be simultaneously included for the optimal design of reservoir operation rules, thus, five measure metrics are chosen as optimization objectives in this paper.

2.1.1 Reliability

Reliability is a widely used concept to describe the probability or frequency of water demand met by water supply from the reservoir (Hashimoto et al., 1982). For a water supply reservoir, the periods in which deliver water is enough to meet demand water are referred as satisfactory periods and the periods when water shortage occurs are referred as failure periods. Reliability is commonly defined as the ratio of the number of satisfactory periods to the number of the total simulation periods (Hashimoto et al., 1982; Moy et al., 1986; Mondal and Wasimi, 2007).

Denote a system's output state by variable X_t at period t, where t=1,2,3….N. In general, the possible values of X_t can be partitioned into two sets: S - the set of all satisfactory periods, and F - the set of all failure periods. The reliability α of a system can be calculated as:

$$\alpha = \text{Prob}\ [X_t \in S] = \frac{\sum_{t=1}^{N} Z_t}{N+1} \tag{1}$$

Where $Z_t = 1$ if $X_t \in$ S, and $Z_t = 0$ if $X_t \in$ F. N is the total number of simulation periods, with a time step of ten days used in this paper. The denominator N+1 is used here as in many studies (Li et al., 2016) with the same assumption as the Weibull quantile estimator, that is, the maximum observed is not the maximum that will ever be observed. Reliability is maximized in this paper.

2.1.2 Resilience

Resilience describes how quickly a system is likely to recover after the occurrence of a failure. Hashimoto et al. (1982) defined the resilience as *the conditional probability that the system is in a satisfactory state in a particular period given that it was in an unsatisfactory state in the preceding period.* Mondal and Wasimi (2007), Chanda et al., (2014) measured it based on the mean duration of consecutive failure sequences. In addition, Moy et al. (1986) proposed another metric of resilience based solely on the maximum duration of the failure sequences over the operating horizon. In this paper, both of the mean and maximum recovery times are adopted to calculate the resilience. For convenience, the resilience objectives ($\gamma_{\_mean}$ and $\gamma_{\_max}$) in this paper are actually measured directly as the mean and maximum recovery times, which are the inverse of resilience defined in the above studies, i.e.:

$$\gamma_{\_mean} = \frac{\sum_{i=1}^{M} T_i}{M} = \frac{\sum_{i=1}^{M} T_i}{\sum_{t=1}^{N} W_t} \tag{2}$$

$$\gamma_{\_max} = \max\left\{T_i\right\} \tag{3}$$

$$\begin{cases} W_t = 1 & X_{t-1} \in S, X_t \in F \quad t > 1 \\ W_1 = 1 & X_1 \in F \quad t = 1 \\ W_t = 0 & otherwise \end{cases} \tag{4}$$

$$\begin{gathered} T_i = p - k \quad 0 < i \leq M \\ if \;\; W_k = 1\,, X_p \in S, \;\; p\ is\ the\ first\ satisfactory\ period\ after\ k \end{gathered} \tag{5}$$

where $\gamma_{\_mean}$ and $\gamma_{\_max}$ are the resilience objectives related to the mean and maximum recover times respectively. T_i represents the duration of the *i*th failure event and M is the total number of failure events. W_t indicates a transition from a satisfactory period to an unsatisfactory one. Both of these two metrics are minimized in this paper.

2.1.3 Vulnerability

Vulnerability is considered to describe the characteristics of the severity of water deficits if a failure occurs. There are a number of metrics of vulnerability in previous research: (1) the mean deficit of each failure period over the operation horizon (Hashimoto et al., 1982; Jain and Bhunya, 2008; Sandoval-Solis et al., 2011; Chanda et al., 2014); (2) the maximum deficit over the operation horizon (Moy et al., 1986; Fowler et al., 2003; Ajami et al., 2008); (3) the probability of exceeding a certain deficit threshold (Mendoza et al., 1997); (4) the return period of a certain level of cumulative deficit (Asefa et al., 2014); (5) the median of all the deficits over the operation horizon (Asefa et al., 2014). In fact, the first two metrics are most popular and they can describe not only the cumulative deficit, but also the extreme failures. Hence, Bayazit and Unal (1990), Srinivasan et al. (1999), Mondal and Wasimi (2007) adopted these two metrics to measure vulnerability, and they are defined in this paper below:

$$v_{\_mean} = \frac{\sum_{t=1}^{N} \frac{D_t - SW_t}{D_t}}{N - \sum_{t=1}^{N} Z_t}, (t = 1, 2, 3 \ldots N) \tag{6}$$

$$v_{\_max} = \max \left\{ \frac{D_t - SW_t}{D_t} \right\}, (t = 1, 2, 3 \ldots N) \tag{7}$$

where D_t is the water demand in period t, and SW_t is the water supply in period t. It is noteworthy that SW_t will never exceed D_t (i.e., the supply water will never be more than what is demanded).

In addition, for the resilience and vulnerability objective, Kjeldsen and Rosbjerg

(2004) suggested using a more stable metric such as the 90th fractile instead of the maximum value. However, for the sake of comparing the results with other studies, this paper still adopts the maximum and mean values, which are the most common metrics in similar researches.

In summary, reliability is measured by α. The inverse of resilience is measured by the mean and maximum durations of failure sequences, i.e., $\gamma_{\_mean}$ and $\gamma_{\_max}$, respectively. Vulnerability is measured by the mean and maximum deficit of the water shortages, i.e., $v_{\_mean}$ and $v_{\_max}$, respectively. All the metrics except α are minimized in the optimization process.

2.2 Reservoir Operating Rule

As shown in Fig. 1 the form of the reservoir operating rule adopted in this paper is the two-point hedging rule modeled after Shih and ReVelle, (1994; 1995), Draper and Lund (2004). In the hedging rule, the water release amount R_t (y-axis) is a function of available water AW_t (x-axis). The release water R_t begins at the origin A and increase linearly with an increasing available water (with a slope of 1.0) until point B, then a linear hedging rule (slope < 1.0) begins from point B to point C after which the demand water (D_t) is fully met. After available water exceeds point D, there will be surplus water (SU_t) due to the upper limit of the reservoir capacity. In this case, R_t equals to the sum of D_t and SU_t. The water supply rule is summarized as below.

$$\begin{cases} R_t = AW_t, & \text{if } AW_t \le \mu_1 \times D_t \\ R_t = \mu_1 D_t + (AW_t - \mu_1 D_t) \times k, & \text{if } \mu_1 \times D_t < AW_t \le \mu_2 \times D_t \\ R_t = D_t, & \text{if } \mu_2 \times D_t < AW_t \le ST_{t+1}^{\max} + D_t \\ R_t = D_t + SU_t, & \text{if } AW_t > ST_{t+1}^{\max} + D_t \end{cases} \tag{8}$$

$$AW_t = S_t + I_t - E_t \quad (9)$$

$$k = (1-\mu_1)/(\mu_2-\mu_1) \quad (10)$$

$$\mu_1 < 1,\ \mu_2 > 1 \quad (11)$$

Where $ST_t^{\max}$ is the minimum storage and maximum storage at period *t;* S_t is the initial water storage at period t; I_t is the inflow to the reservoir at period t; E_t is the evaporation of the reservoir at period t; k is the slope of line BC; μ_1 and μ_2 are two parameters that decide where the hedging starts and ends respectively. Hence, the values of μ_1 and μ_2 at different operation periods are regarded as the key points of hedging and are optimized in this paper. Note that Fig.1 shows the hedging rule for only one operation period. As a separate rule is optimized for each period of the year, there are totally 2×*P* parameters need to be optimized where *P* represents the number of operation periods divided in one calendar year. Because of the characteristic of hedging (Shih and ReVelle, 1995), μ_1 is smaller than 1 and μ_2 is greater than 1.

2.3 Constraints

For the reservoir operation optimization, the constraints conclude:

$$S_{t+1} = S_t + I_t - E_t - R_t \quad (12)$$

$$ST_t^{\min} \le S_t \le ST_t^{\max} \quad (13)$$

$$0 \le SW_t \le D_t \quad (14)$$

where $ST_t^{\min}$ and $ST_t^{\max}$ are the minimum storage and maximum storage at period t; SW_t is the supply water at period t. It should be noted that when there is no surplus water, release water R_t equal to supply water SW_t.

2.4 Optimization Method

In recent years, many-objective evolutionary algorithms have been developed, such as MOEA/D (Zhang and Li, 2007), ABYSS (Nebro et al., 2008), and ε-NSGAII (Kollat and Reed, 2006), and have been proved effective for solving complex engineering problems with more than three conflicting objectives. In this paper, the ε-NSGAII is selected to solve the reservoir operation optimization problem as it has been tested on different engineering optimisation problems (Kollat and Reed, 2006; Kasprzyk et al., 2009; Kollat et al., 2011; Kasprzyk et al., 2012; Fu et al., 2012; Fu et al., 2013; Wang et al., 2014; Chu et al., 2015). Table 1 shows the parameter values of the algorithm used in this paper, which are determined according to the values suggested in the literature. The epsilons were determined through trials to achieve the balance of a clear view of the solutions and a good representation of the Pareto fronts. Because of the random nature, ten random-seed runs were used to solve the reservoir optimal operation problem. For each random-seed run ε-NSGAII is implemented for 500,000 model evaluations. The Pareto approximate set analyzed in this paper was generated across all ten random-seed optimization runs.

3 Case Study

In this paper, a water supply reservoir called Biliu River Reservoir is taken as a case study to illustrate the relationships among reliability, resilience and vulnerability criteria. The Biliu River Reservoir located in the Liaoning Province of China is the most important water source for Dalian, Liaoning Province (Li et al., 2016). The reservoir has an active storage capacity of 714 million m^3 and a minimum storage capacity of 70 million m^3 while the active storage capacity changes to 665 million m^3 in flood seasons for the purpose of flood control. The main operation purpose of the Biliu River Reservoir is to meet the industrial and domestic water demands in Dalian, with a total of 230 million m^3 each year. As the agricultural and ecological demand is quite small, they are not taken into account for simplicity. The reservoir inflow data and the simulation horizon is from 1958 to 2013. One calendar year is divided into 3x12= 36 periods where the first two periods of each month have 10 days and the third period consists of the remaining days in each month. Hence, 2016 periods are totally included in the simulation model, which is considered long enough according to Bayazit and Unal (1990), Peng et al. (2015), Li et al. (2016). During this period the average annual inflow is 556 million m^3 with an extremely uneven temporal distribution.

It is noteworthy that there are some details refer specifically to this case study versus the generic method introduced in section 2. Firstly, in this study each simulation period contains only 10 days (11 days or 8 days), and there are a total of 2016 simulation periods over the operating horizon. It is assumed that the reservoir operators generally consider that the negative impact of a water deficit event will last for one or two months, i.e., 3-6 periods in this paper, thus five periods are used as the minimum length between two different failure sequences. Hence, the variable W_t is changed to W_t^S in this case study and is accounted as:

$$\begin{cases} W_t^S = 1,\ X_t \in F, X_{t-1}, X_{t-2}, X_{t-3}, X_{t-4}, X_{t-5} \in S & t > 5 \\ W_t^S = 1,\ X_t \in F, and\ this\ is\ the\ first\ failure\ period & t \leq 5 \\ W_t^S = 0 & otherwise \end{cases} \tag{15}$$

Meanwhile, the mathematical definition of T_i in equation (5) is changed as:

$$\begin{gathered} T_i = p - k + 1 \quad 0 < i \leq M,\ p > k \\ if\ \ W_k^S = 1\ , W_p^E = 1, p\ is\ the\ first\ transition\ period\ after\ k \end{gathered} \tag{16}$$

Where W_p^E indicates a transition from an unsatisfactory period to a satisfactory one and is accounted as:

$$\begin{cases} W_t^E = 1, X_t \in F, X_{t+1}, X_{t+2}, X_{t+3}, X_{t+4}, X_{t+5} \in S & t \leq N - 5 \\ W_t^E = 1, X_t \in F, and\ this\ is\ the\ last\ failure\ period & t > N - 5 \\ W_t^E = 0 & otherwise \end{cases} \tag{17}$$

Consider, for example, the following two cases of operational sequences of 12 periods:

- Case 1: X_t = (…,F,F,F,F,S,S,S,S,F,F,F,F,…)
- Case 2: X_t = (…,F,F,F,F,S,S,S,S,S,F,F,F,…)

In the first case, there are only one set of consecutive failure because the two four-period sequences are at a distance of four periods. Thus, the duration of the consecutive failures T_i in case 1 is equal to 12. In the second case, there are two sets of consecutive failure because there are five continuous satisfactory periods between the two failure sequences.

Secondly, the operating rule introduced in section 2.2 is specific to this case study. As the main objective of water supply is to meet industrial and domestic demands, the operators of Biliu River Reservoir is required to supply at least 80% of the demand amount except for extremely drought periods. Thus, μ_1 is assumed to be 0.8 (i.e., hedging could only be executed when available water exceeds 80% of demand water).

Hence, only the values of μ_2 at different operation periods need to be determined and therefore only P=36 variables need be optimized in the case study rather than 2×P. In addition, two alternative scenarios (values of μ_1 =0.4 and 0.6) are tested in section S1 of the supplemental material. By comparing three scenarios, it is demonstrated that the value of μ_1 has little influence on the relationships obtained in this paper.

4 Results and Discussion

The approximate Pareto-optimal set with 2497 solutions is obtained and section S2 in supplemental material shows the convergence results of the optimization. It is first analyzed in a global view of the five objectives and then it is explored in lower-dimensional space to analyze the relationships among the performance criteria. This allows for comparison of the solution sets from different dimensions including reliability-vulnerability, reliability-resilience, and resilience-vulnerability as detailed below.

4.1 Five-Dimensional Objective Tradeoffs

A global view of the five-objective tradeoffs is first analyzed to illustrate the relationships between the five objectives. The reliability objective α, vulnerability objective $v_{\_mean}$, resilience objective $\gamma_{\_mean}$ are plotted on the x-axis, y-axis, and z-axis, respectively. The vulnerability objective $v_{\_max}$ is shown by the color of the spheres ranging from blue to red, representing the values from 0.180 to 1.000. The resilience objective $\gamma_{\_max}$ is shown by the size of the spheres which varies from 20 to 120. The large spheres represent high values of $\gamma_{\_max}$ and small spheres represent low values. An ideal solution would be located toward the front lower corner (high α, low $v_{\_mean}$, low $\gamma_{\_mean}$) of the plot in Fig. 2 and represented by a small (low $\gamma_{\_max}$), blue (low $v_{\_max}$) spheres. The arrows in Fig. 2 highlight directions of increasing preference.

There are three different regions in the objective space. Region i in Fig. 2 captures higher α (>0.92), with higher $\gamma_{\_mean}$ (>17), and higher $v_{\_mean}$ (>0.08), meanwhile, $\gamma_{\_max}$ and $v_{\_max}$ are relatively high as shown by the big sizes and warm colors of spheres. This explains that a high reliability of water supply may result long duration and high severity of water shortage. Region ii captures solutions with higher α (> 0.92), higher $v_{\_mean}$ (> 0.08), and the mean duration of failures varies from 5 to 10. However, these solutions can have a wide range of $v_{\_max}$ as illustrated by their colors from green (0.59) to red (1.00) while the solutions also have a wide range of $\gamma_{\_max}$ as illustrated by the size from small (60) to large (120). Region iii in Fig. 2 is composed of solutions with low α and low $v_{\_mean}$, and $\gamma_{\_mean}$ is in a range from 5 to 10. Similar to the solutions in region ii, these solutions also have a wide range of $\gamma_{\_max}$ and $v_{\_max}$. This highlights the importance of considering the maximum of duration and deficit of water shortage in the optimization process. The correlation coefficients among five objectives are shown in Table S1 of the supplemental materials. α and $v_{\_mean}$ are highly correlated but they strongly conflict, which makes it important to include them in the optimization to reveal the their tradeoff. All other pairs of objectives have weak correlations, suggesting that they don't provide duplicate information and should all be included. This is consistent with the study by Kjeldsen and Rosbjerg (2004) in which removing either vulnerability or the inverse of resilience was suggested because they are highly correlated and do not conflict.

4.2 Reliability versus Vulnerability

This section aims to analyze the relationship between reliability (α) and vulnerability ($v_{\_mean}$ and $v_{\_max}$) criteria. Fig. 3. shows the full suite of Pareto approximate solutions in different 2D plots.

In Fig. 3(a), a clear tradeoff curve between α and $v_{\_mean}$ can be observed and it represents the approximate Pareto front had only these two objectives been used for optimization (highlighted with red squares). The conflicting relationship between α and $v_{\_mean}$ can be explained by the different degrees of hedging. To illustrate how hedging rule influences the performance criteria clearly, three solutions located in different regions on the tradeoff curve (highlighted with circles) are selected. The different hedging parameters of three solutions are shown in Fig. 4(a). As explained in section 2.2, each hedging rule contains 36 key decision variables, i.e., μ_2 in 36 periods. These variables determine the degree of hedging. The larger the value of μ_2, the higher the degree of hedging is.

Comparing Fig. 3(a) and Fig. 4(a), solutions with a higher α and $v_{\_mean}$ generally have smaller values of μ_2 (i.e., lower degrees of hedging). This result confirms the finding by Bayazit and Unal (1990) that an increasing degree of hedging leads to a reduction in reliability. It is because that the solutions with lower degrees of hedging tend to supply as much water as required at the current period, resulting in a fewer number of failures but more serious ones in the following periods should they occur. On the opposite, for solutions with higher degrees of hedging, more water is stored in the reservoir at the current period and this reduces the severity of water shortage in the future, resulting in low reliability and vulnerability. As shown in Fig. 4(a), the value of μ_2 seems very large in some periods. For example, it equals to nearly 100 in Solution 3 at the 28th period. In this case, it means the reservoir don't release the full demand until the available water for the reservoir exceed 639 ($\mu_2 \times D_t$) million m^3 which is about 90% of the active storage capacity. It is reasonable to limit water supply at this time because the storage is not full of water at the end of flood season.

To express it further, the average values of SW_t (supply water)/ D_t (demand water) in 36 periods over 56 years are shown in Fig.4 (b). Comparing three curves, the solution with the highest α and $v_{\_mean}$ (Solution 3 colored by green) tends to supply more water because the degree of hedging is low. While the solution with the lowest α and $v_{\_mean}$ (Solution 1 colored by blue) tends to supply less water because the degree of hedging is high. These two figures also show that when μ_2 is large the supply water is low. For example, Solution 3 has a very large value of μ_2 in the 29th period, and the corresponding value of SW_t/D_t is low as shown in Fig. 4(b).

Fig. 3(b) shows that the tradeoff exists in the objective space of α and $v_{\_max}$ with the Pareto approximate solutions highlighted with orange squares when α >0.925. But the tradeoff is not obvious compared to Fig. 3(a). In other regions of Fig.3 (b), there is no observable relationship between α and $v_{\_max}$. The three points shown in Fig.3(a) are also shown in Fig.3 (b) highlighted with circles. All the three solutions are not located on the tradeoff curve in the α and $v_{\_max}$ space, which means they are dominated. It can also be found that $v_{\_max}$ has a wide range of values. Prior research (Moy et al. 1986; Bayazit and Unal, 1990) reported a conflicting relationship between α and $v_{\_max}$. However, the thresholds where the tradeoff exists may be different from system to system due to some factors, such as the simulation periods, reservoir inflow, water demand and so on.

In Fig. 3(c), $v_{\_mean}$ and $v_{\_max}$ can achieve the best value at the same point which is highlighted by a yellow square. It seems no obvious relationship exists between these two objectives. The three points shown in Fig.3(a) are also shown in Fig.3 (b) highlighted with circles. Except Solution 1 the other solutions are far away from the bottom left corner. The two vulnerability objectives have different responses to the operation rules. Hence, they should be considered simultaneously in identifying high performing solutions. This pair of relationship can explain why we should use two metrics to measure vulnerability.

4.3 Reliability versus Resilience

This section aims to analyze the relationship between reliability (α) and resilience criteria ($\gamma_{\_mean}$ and $\gamma_{\_max}$). As illustrated in section 4.1, α and $\gamma_{\_mean}$ have an obvious relationship while $\gamma_{\_max}$ has no obvious relationship with others.

Fig. 5(a) shows the Pareto approximate set in the objective space of α and $\gamma_{\_mean}$. Different relationships between α and $\gamma_{\_mean}$ are observed from the two sides divided by a line where α approximately equals to 0.845. There is a close synergetic relationship between α and $\gamma_{\_mean}$ on the underside of the critical region, where $\gamma_{\_mean}$ decreases with an increase in α. However, there is a clear tradeoff between α and $\gamma_{\_mean}$ on the upside of the critical region, where $\gamma_{\_mean}$ increases with an increase in α. That means less hedging (more reliable solutions) increases the conflicting relationship between α and $\gamma_{\_mean}$. The tradeoff curve between α and $\gamma_{\_mean}$ can be observed, which represents the approximate Pareto front had only these two objectives been used for optimization (highlighted with blue squares). As shown in Fig.S1 of the supplemental materials, along with the decreasing of the parameter μ_1 the range of the conflicting relationship between α and $\gamma_{\_mean}$ becomes smaller. That would also demonstrate that hedging decreases the conflict relationship because the smaller value of μ_1 means more hedging. More details about this interesting phenomenon is analyzed in the supplemental materials.

A complex and nonlinear relationship between α and $\gamma_{\_mean}$ is revealed with the case study and it can be attributed to the impact of hedging on $\gamma_{\_mean}$. On the upside of the critical region, the reliability α is high and the degree of hedging is low, resulting in less failure periods. In this case, with the decreasing degree of hedging (increasing along with x-axis), the number of the total failure periods decreases but the mean duration in one continuous failure sequence increases, i.e., the failure periods come out more intensively. That is because the reservoir supplies more water for the current periods and induces a more durable and more intense failure event in the dry periods.

On the underside of the critical region, the reliability α is low and the degree of hedging is high, resulting in more failure periods. In this case, with the increasing degree of hedging (decreasing along with x-axis), many unnecessary limits for water supply happen in wet periods, i.e., water supply limits are carried out too frequently in the periods with enough available water. This may reduce the duration of failures in dry periods, but it can result in longer duration of failures in wet periods.

Fig. 5 (b) shows that $\gamma_{\_max}$ has no obvious relationship with α, implying that they represent different aspects of system performance and have to be considered simultaneously for system assessment. It can also be observed that the solutions on the tradeoff curve of α and $\gamma_{\_mean}$ (highlighted with blue squares in Fig. 5(a) also shown in Fig.5 (b)) all have middle or high values of $\gamma_{\_max}$. Similarly, three solutions located in the bottom right corner of Fig.5. (b), represented by red colors, are considered the best in the objective space of α and $\gamma_{\_max}$. However, they are dominated by the Pareto-optimal solutions in the space of α and $\gamma_{\_mean}$. Fig. 5 (b) also shows that the range of $\gamma_{\_max}$ is small and the value is low only when α is relatively low.

4.4 Resilience versus Vulnerability

This section aims to analyze the relationships between vulnerability ($v_{\_mean}$ and $v_{\_max}$) and resilience ($\gamma_{\_mean}$ and $\gamma_{\_max}$) criteria through pairwise comparisons, as shown in Fig.6.

As shown in Fig.6 (a), the relationship between $v_{\_mean}$ and $\gamma_{\_mean}$ is similar with that between α and $\gamma_{\_mean}$. The mean deficit $v_{\_mean}$ and the mean duration of failures

$\gamma_{\_mean}$ can be conflicting or synergetic at different regions. Comparing Fig.5 (a) and Fig.6(a) shows that there exists a similar critical region where the relationship changes from tradeoff to synergy. On the right side of the critical region, $\gamma_{\_mean}$ has a conflicting relationship with $v_{\_mean}$ while the relationship is opposite on the left side of the critical region. As illustrated in sections 4.2 and 4.3, this is because that the degree of hedging has different impacts on $\gamma_{\_mean}$ and $v_{\_mean}$. In general, there exist both synergetic and conflicting relationships between $\gamma_{\_mean}$ and $v_{\_mean}$ .Fig. 6 (b) shows that $\gamma_{\_max}$ has no obvious relationship with the mean deficit $v_{\_mean}$. It also shows that $\gamma_{\_max}$ has a wide range of values along with the x-axis. In Fig.6. (c), there is no tradeoff and no synergy between $\gamma_{\_mean}$ and $v_{\_max}$. This result is different from the study by Bayazit and Unal (1990). In Fig.6 (d), there is still no obvious relationship between $v_{\_max}$ and $\gamma_{\_max}$ although a tradeoff was reported in the study by Bayazit and Unal (1990). In summary, the maximum of resilience and vulnerability seem to have no obvious relationship with other objectives.

4.5 Discussion

Comparing the relationship developed in this paper to the previous studies, there are some common points and also some different points. For reliability criterion α and vulnerability criterion $v_{\_mean}$, the tradeoff in this paper is in agreement with the studies by Hashimoto et al. (1982) and Bayazit and Unal (1990). For reliability criterion α and vulnerability criterion $v_{\_max}$, the conflicting relationship exists both in this paper and that of Moy et al. (1986) and Bayazit and Unal (1990) but the range of this relationship is a little different. The same relationship in different case studies can demonstrate the generalization of the results to some extent.

The most different finding in this paper is the relationship associated with mean resilience criterion $\gamma_{\_mean}$ which is shown in Fig.5(a) and Fig.6(a). In the previous studies, a conflicting relationship existed between resilience criterion $\gamma_{\_mean}$ and vulnerability criterion $v_{\_mean}$, while a synergetic relationship existed between resilience criterion $\gamma_{\_mean}$ and reliability criterion α. However, the results from this study show a more complex relationship. The relationship between α and $\gamma_{\_mean}$ exhibits both tradeoff and synergy and there exists a critical region denoting a transition from synergy to tradeoff, which is very different from that reported in the previous literature. Hashimoto et al. (1982) and Bayazit and Unal (1990) reported only the synergetic relationship between α and $\gamma_{\_mean}$. Note that the conflicting relationship in this study exists in the critical region where the reliability α is high and these solutions are generally preferred by operators and more likely to be used in practice. Similarly, there exist both synergetic and conflicting relationships between $\gamma_{\_mean}$ and $v_{\_mean}$. However, the conflicting relationship between these two metrics was observed previously by Hashimoto et al. (1982) and Bayazit and Unal (1990), while the synergetic relationship was observed separately by Kundzewicz and Kindler (1995) and Kjeldsen and Rosbjerg (2004). It could be concluded that when a highly reliable operation policy is selected, both resilience and vulnerability performance become worse. Thus, the finding obtained in this study provides a more useful and complete picture of the relationship among α,

$\gamma_{\_mean}$ and $v_{\_mean}$. Meanwhile, it provides an informed decision support for reservoir managers.

For other pairs of objectives containing maximum vulnerability criterion $v_{\_max}$ and maximum resilience criterion $\gamma_{\_max}$, there is no obvious relationship explored in this paper. This is also different from the finding from Bayazit and Unal (1990) and Srinivasan et al. (1999).

The results obtained in this paper show more complex and more complete relationships which contain some critical transitions from tradeoff to synergy (or from synergy to tradeoff) are developed in this paper. Some detailed description of the relationship among five objectives show that decision makers shouldn't ignore any of them when operating reservoirs. It should be noted that an interesting critical region exists where the relationship of reliability resilience and vulnerability criteria transforms shown in Figure 5(a) and 6(a). The solutions located here are more likely to be preferred by operators because all the objectives of α , $\gamma_{\_mean}$ and $v_{\_mean}$ seem to achieve satisfying values in this region. The full description of the relationship can provide an informed perspective for water supply system. However, how to use the relationship depends on the preference of different decision makers and the features of the system.

5 Conclusions

This paper used a many-objective visual analytics approach to reveal and explore the relationships among three performance criteria in water supply systems, i.e., reliability, resilience and vulnerability. The many-objective analytics approach consists of a many-objective evolutionary algorithm (ε-NSGAII) and an interactive visual analytics tool. To measure a more comprehensive performance of the system, a suite of five objectives are considered: (1) maximizing the reliability of water supply , i.e., α, (2) minimizing the mean deficit of water supply, i.e., $v_{\_mean}$, (3) minimizing the maximum deficit of water supply, i.e., $v_{\_max}$ (4) minimizing the mean duration of water shortage, i.e., $\gamma_{\_mean}$ and (5) minimizing the maximum duration of water shortage, i.e., $\gamma_{\_max}$. A case study of the Biliu River Reservoir located in northeast China was used to analyse the relationships between the objectives.

The results from the case study show more complex relationships between reliability, resilience and vulnerability than previously reported. The results can be summarized below:

(1) The reliability criterion α has a conflicting relationship with vulnerability criteria ($v_{\_mean}$ and $v_{\_max}$), which is in agreement with the previous research.

(2) The reliability criterion (α) has both a synergetic relationship and a conflicting relationship with the resilience criterion ($\gamma_{\_mean}$) in different regions of the solution space. A similar relationship is also found between the resilience criterion ($\gamma_{\_mean}$) and the vulnerability criterion ($v_{\_mean}$). This reveals a more complete relationship among the three criteria compared to that reported in previous research. The newly discovered relationships exist in the region where these solutions are generally preferred by operators and more likely to be used in practice.

(3) There is no obvious tradeoff or synergy in other pairs of criteria, which is generally same as that in previous studies.

This study demonstrates the benefits of using advanced many-objective optimization. This approach can provide a large number of Pareto-optimal solutions, which allows for exploring a full picture of the relationships between any objectives in a lower dimensional space. Furthermore, this analysis approach is suggested as one way forward to address the challenges in the context of revealing and balancing the tradeoffs between various objectives in complex water supply systems.

Note that the results reported above were obtained from the case study of the Biliu reservoir, their generalizability should be carefully considered with more evidence from different case studies. In particular, future work will involve some more complex systems such as multi-reservoir systems and the relationships between reliability, resilience and vulnerability criteria might be affected by the interdependency of multiple reservoirs.

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Table1. Parameter Values of the ε-NSGAII Algorithm

Symbol	Value	Description
n_{initial}	12	Initial population size
n_{maximum}	500000	Maximum number of model simulations
η_{m}	20	Distribution index for mutation
η_{c}	15	Distribution index for crossover
	0.01	Objective resolution: reliability objective α
	0.1	Objective resolution: resilience objective $\gamma_{\_mean}$
ε	0.1	Objective resolution: resilience objective $\gamma_{\_max}$
	0.01	Objective resolution: vulnerability objective $\nu_{\_mean}$
	0.01	Objective resolution: vulnerability objective $\nu_{\_max}$

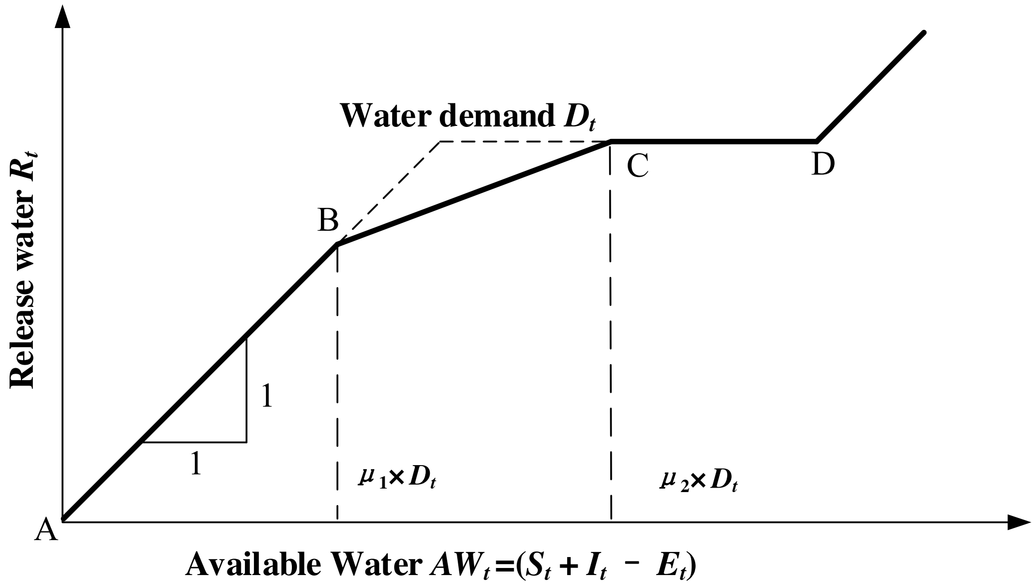

Fig. 1. A Two-point hedging rule

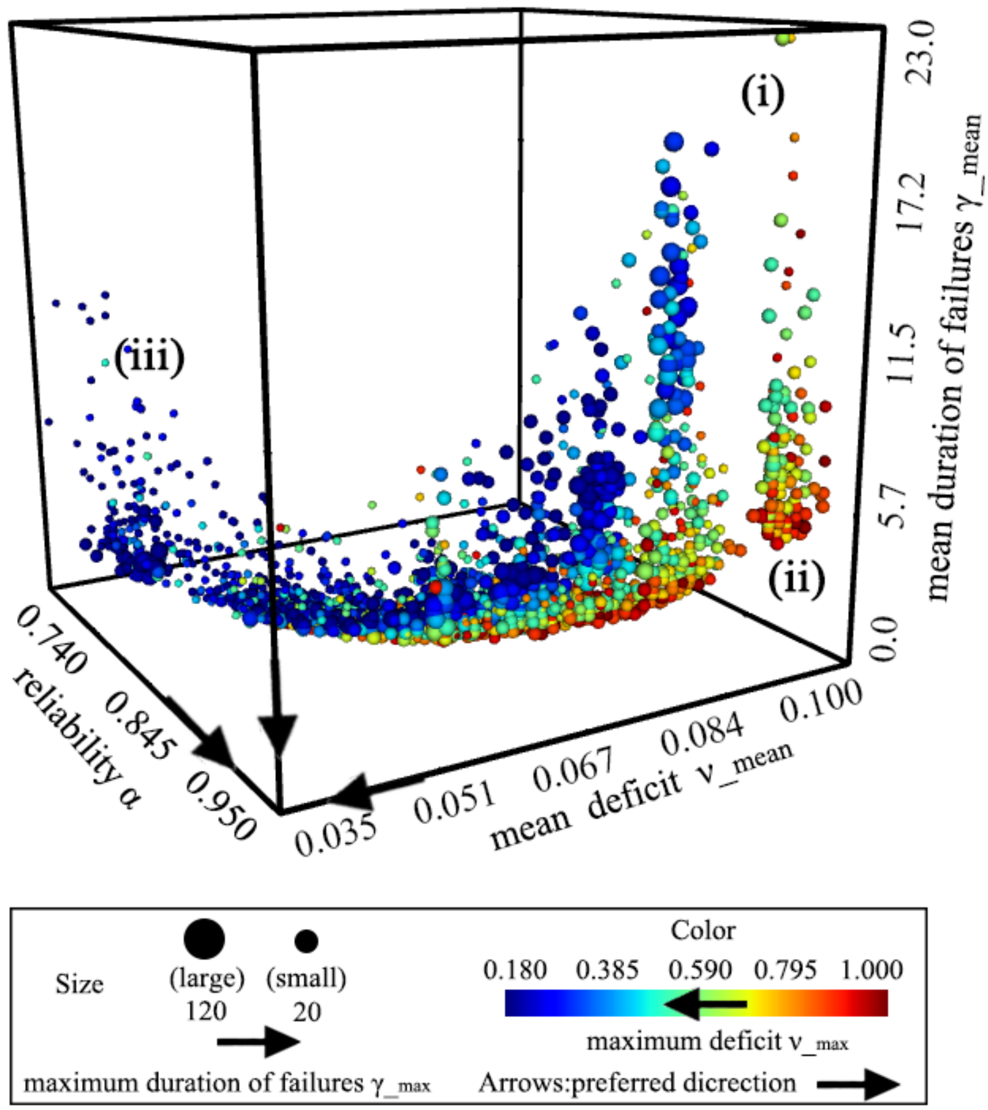

Fig. 2. Approximate Pareto solutions from five-objective optimization, with arrows showing directions of increasing preference

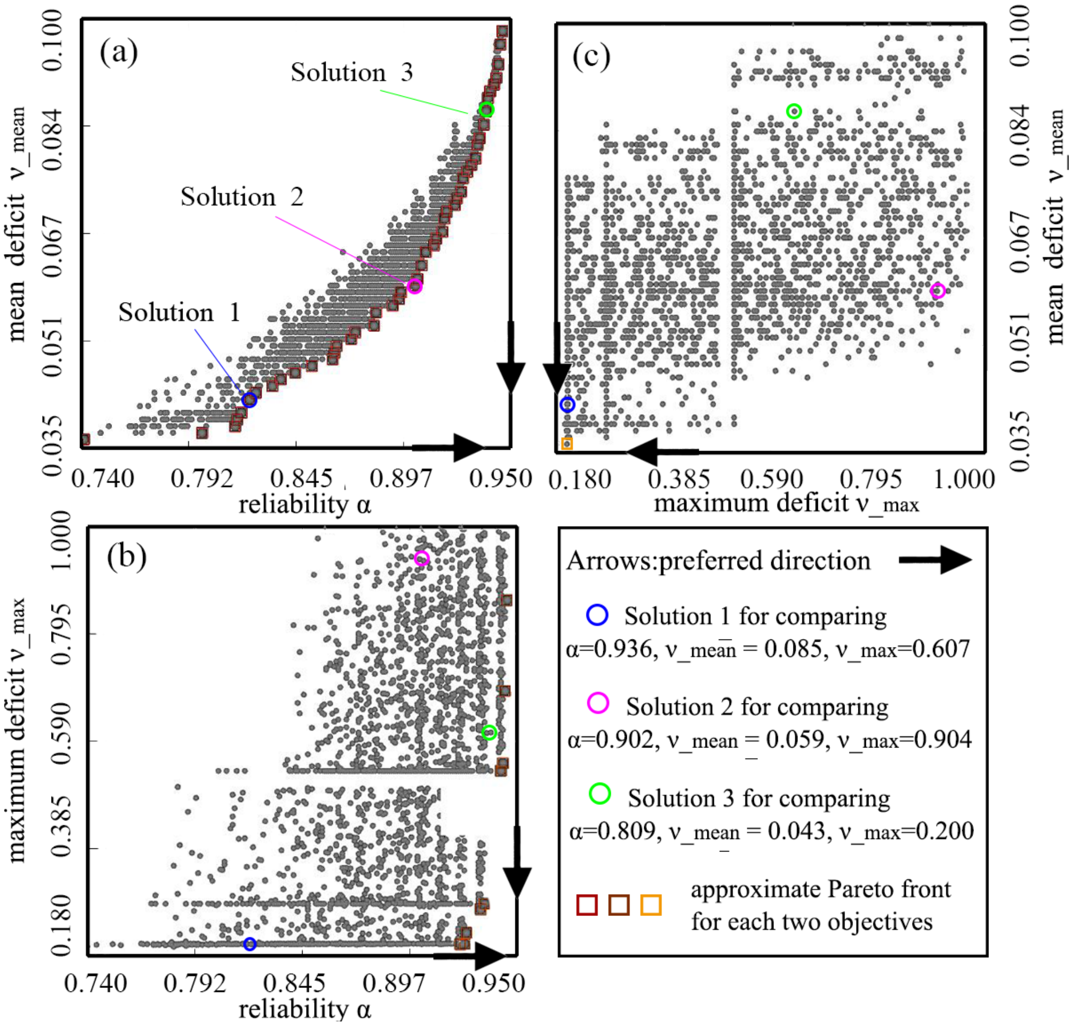

Fig.3. Low-dimensional tradeoffs between reliability and vulnerability criteria: (a) reliability α versus mean deficit $v_{\_mean}$; (b) reliability α versus maximum deficit $v_{\_max}$; (c) $v_{\_mean}$ versus maximum $v_{\_max}$.

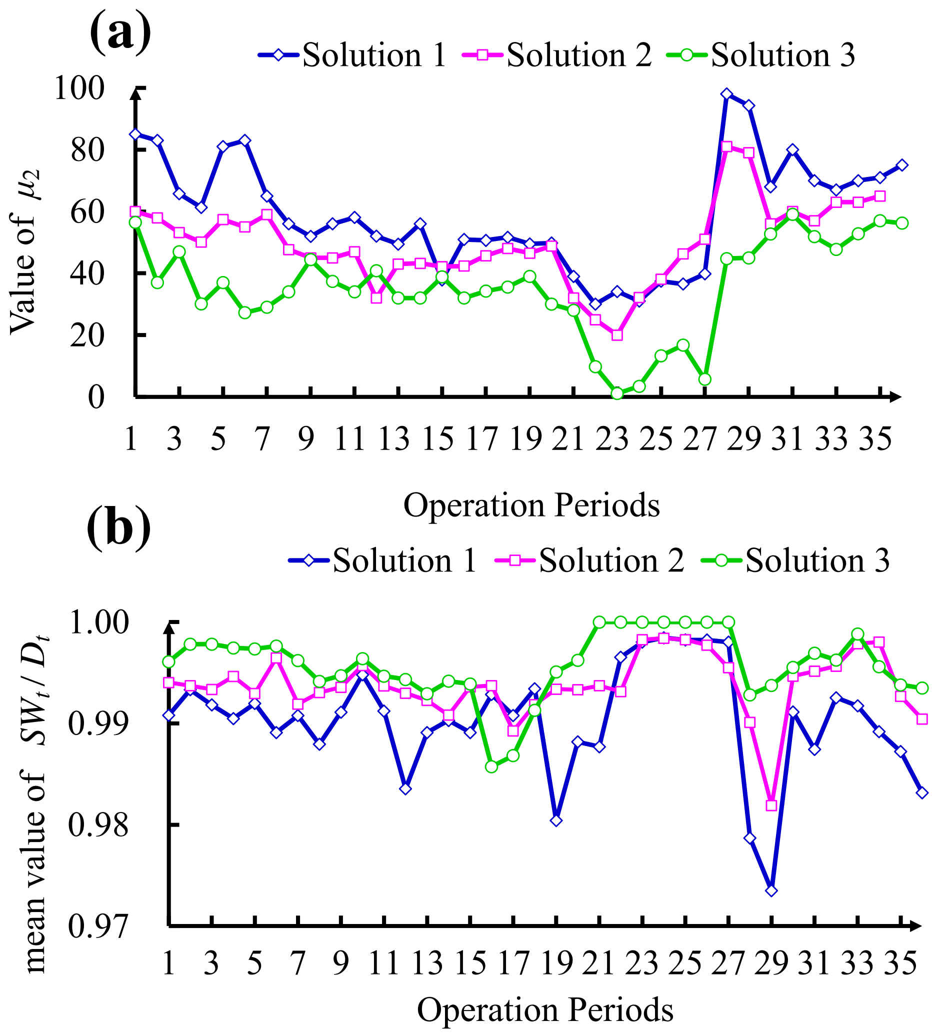

Fig.4. Analysis for three selected solutions from the Pareto approximate set: (a) the value of parameter μ_2 in 36 periods (b) the average value of SW_t (supply water)/ D_t (demand water) in 36 periods

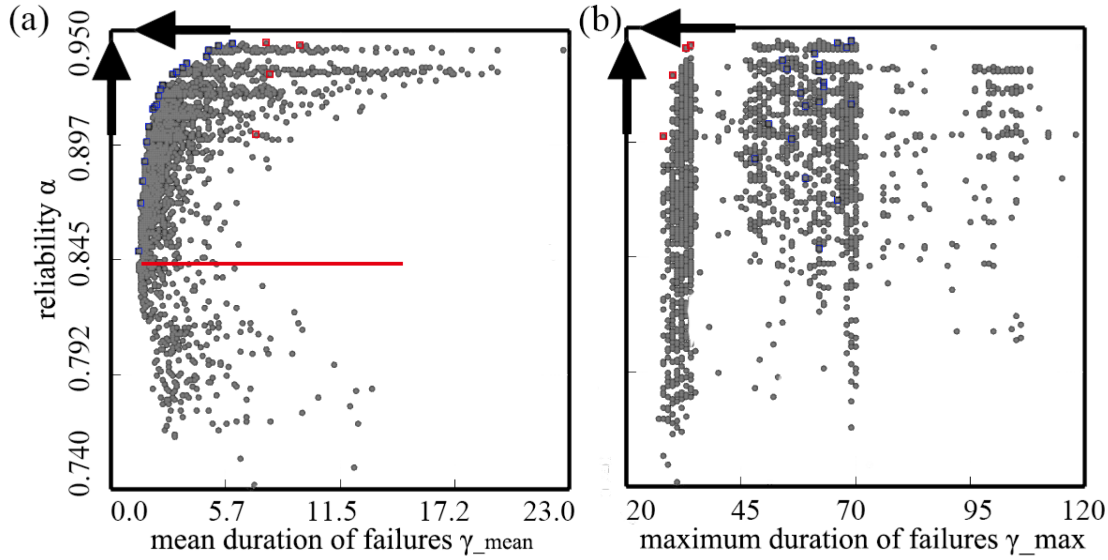

Fig. 5. Low-dimensional tradeoffs for reliability and resilience criteria: (a) reliability α versus mean duration of failures $\gamma_{\_mean}$; (b) reliability α versus maximum duration of failures $\gamma_{\_max}$.

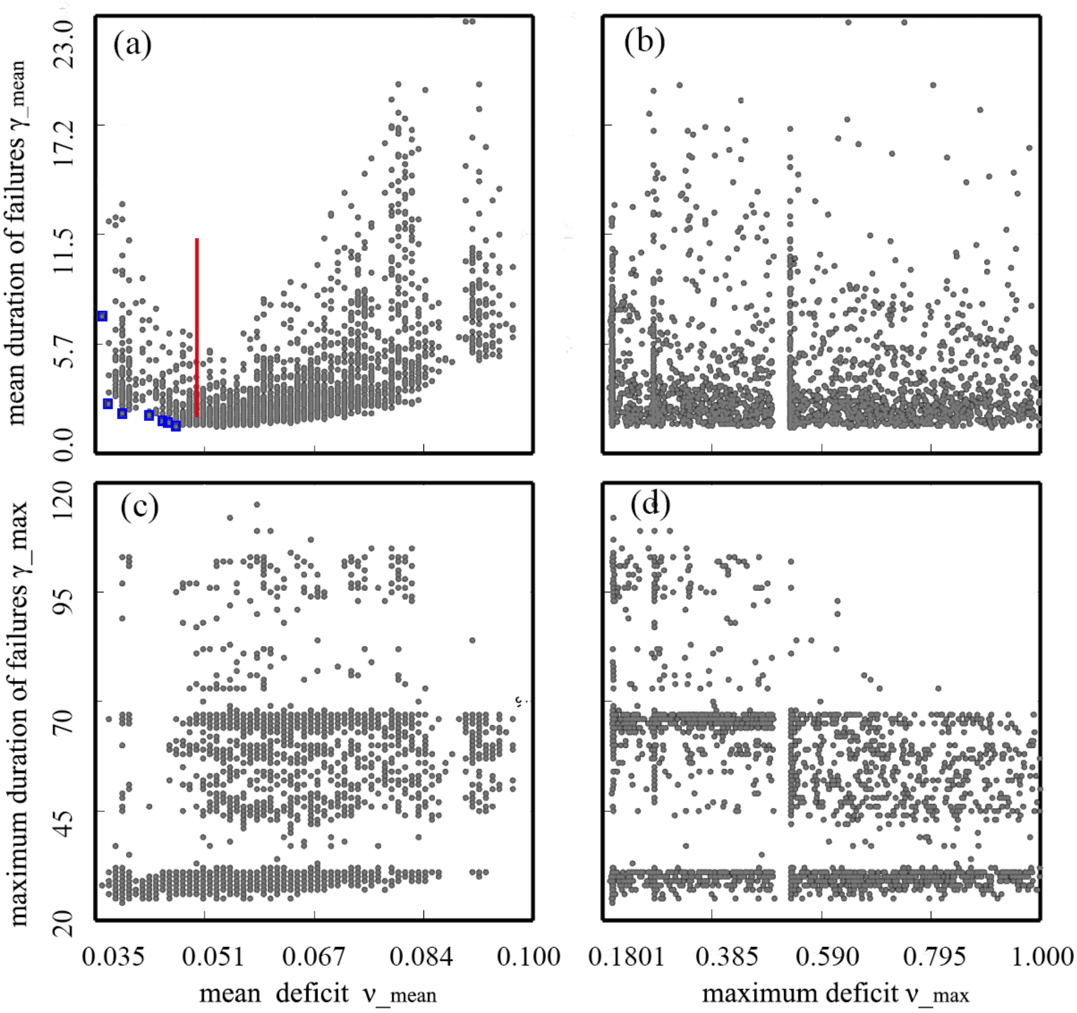

Fig. 6. Low-dimensional tradeoffs for vulnerability and resilience criteria: (a) mean deficit $\nu_{\_mean}$ versus mean duration of failures $\gamma_{\_mean}$ (b) maximum deficit $\nu_{\_max}$ versus mean duration of failures $\gamma_{\_mean}$; (c) mean deficit $\nu_{\_mean}$ versus maximum duration of failures $\gamma_{\_max}$; (d) maximum deficit $\nu_{\_max}$ versus maximum duration of failures $\gamma_{\_max}$

Supplemental Materials

1. Sensitivity analysis of parameters μ_1 in the operation rule

As the main object of water supply is industrial and domestic demands, the operators of Biliu River Reservoir is required to supply at least 80% of the demand amount except for extremely drought periods. Thus, μ_1 is assumed to be 0.8 (i.e., hedging could only be executed when available water exceeds 80% of demand water) in this paper. Hence, only the values of μ_2 at different operation periods need to be determined and 36 variables are totally to be optimized in the case study.

To discuss whether this assumption will influence the results, two alternative scenarios (values of μ_1 =0.4 and 0.6) are tested. The scenarios with the value of μ_1 = 0.8, 0.6, 0.4 are denoted by S1, S2 and S3, respectively. For simplicity, only the most important findings, i.e., the relationships among reliability α, mean vulnerability objective $v_{\_mean}$ and mean resilience objective $\gamma_{\_mean}$, are shown. The results of three scenarios are shown in Fig. S1.

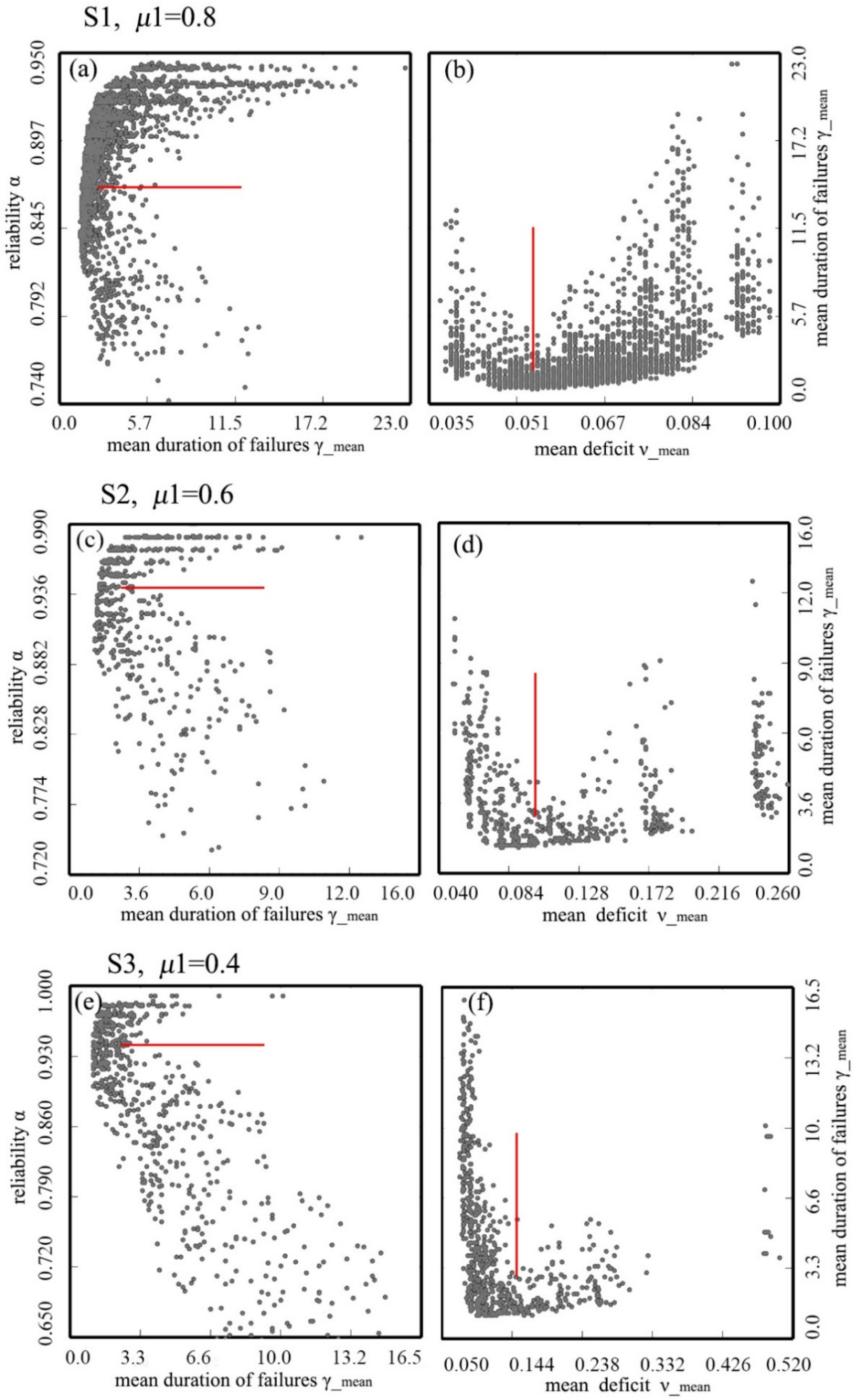

Fig. S1 Comparison of the results from S1, S2 and S3

As can be seen from Fig S1, in each scenario, $\gamma_{\_mean}$ has a synergy relationship with α on the left side of a critical region, and this relationship changes to competitive on the right side. While this phenomenon is exactly opposite for the relationship between $\gamma_{\_mean}$ and $\nu_{\_mean}$. The difference in three figures is the location of the critical region. In scenario 1, the critical region located near the solutions with a middle value of reliability α. This value increases from scenario 1 to scenario 3. However, all the three scenarios have the similar relationships, which are different from previous studies and are one of our main findings. Based on the results, it can be concluded that different forms of the operation rule can't influence the general shape of the relationships in this paper though it may change some details and thresholds of the relationships.

In addition, it could be found that along with the decreasing of the parameter μ_1 (from S1 to S3) the range of the conflicting relationship between α and $\gamma_{\_mean}$ becomes smaller. That would demonstrate that hedging decreases the conflict relationship because the smaller value of μ_1 means more hedging. However, conflict always remains at the highest reliabilities, where operations would normally be. It could concluded that the conflicting relationship between α and $\gamma_{\_mean}$ is important and the conflicting region becomes smaller with more hedging.

2. Statistics analysis for the optimization quality

In this paper, ten random-seed runs were used to solve the reservoir optimal operation problem due to the random nature. For each random-seed run ε-NSGAII is implemented for 500,000 model evaluations. The Pareto approximate set analyzed in this paper was generated across all ten random-seed optimization runs. For guaranteeing that the optimization converged, three statistics metrics (i.e., Hyper-volume, Generational Distance, Additive Epsilon Indicator) of the ten optimization process are calculated. From the statistical metrics, it can be concluded that all the optimizations have converged. The result is shown as below.

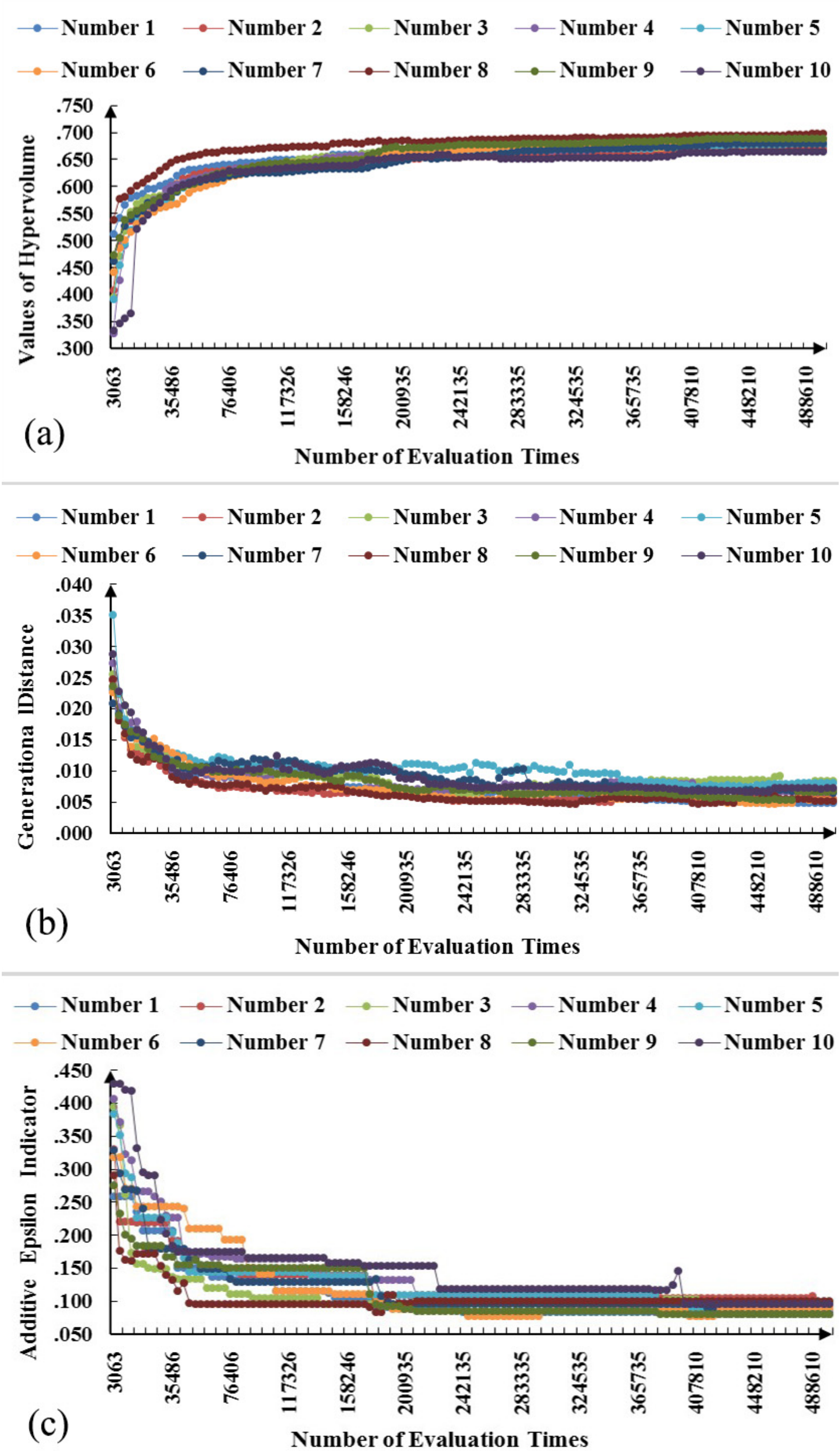

Fig. S2 Statistics values of the ten optimization processes：(a) Hyper-volume, (b) Generational Distance, (c) Additive Epsilon Indicator

3. Correlation coefficients among five objectives

For illustrating the relationship furthermore, the overlaps (or called dependence) among different objectives are calculated in terms of the correlation coefficient between the 2497 solutions obtained from 10 optimization runs. There are totally 5 objectives, and hence, there are 10 groups of double-objective need to be calculated. The correlation coefficients is calculated as:

$$\rho = \frac{\mathrm{cov}\left\{Obj_1, Obj_2\right\}}{\sqrt{\left(\mathrm{var}\left\{Obj_1\right\} \times \mathrm{var}\left\{Obj_2\right\}\right)}} \quad (1)$$

The higher the value of the correlation coefficient, the more the two considered objectives overlap. The result is shown in Table S1. Expect the pair of reliability α and mean vulnerability $v_{\_mean}$, all the other correlation coefficients are less than 0.5, which demonstrate that these pairs have no obvious correlations. Some pairs of objectives are uncorrelated, such as $\gamma_{\_mean}$ and $v_{\_max}$. Some other pairs of objectives have weak correlation coefficients because they contain both conflict and synergy, such as α and $\gamma_{\_mean}$. However, α and$v_{_mean}$ are highly correlated because they strongly conflict, and it is important to include both to reveal the tradeoff between them. The weak correlation across all of the other combinations suggests that they don't provide duplicate information and should all be included.

Table S1. Correlation coefficients between five objectives

	α	$v_{\_mean}$	$v_{\_max}$	$\gamma_{\_mean}$	$\gamma_{\_max}$
α	1	0.924	0.462	0.346	0.284
$v_{\_mean}$	-	1	0.461	0.482	0.252
$v_{\_max}$	-	-	1	-0.058	-0.286
$\gamma_{\_mean}$	-	-	-	1	0.111
$\gamma_{\_max}$	-	-	-	-	1