Evaluating the robustness of water quality sensor placement strategies of water distribution systems considering possible sensor failures and system changes

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Abstract

An early contamination warning system with deployed water quality sensors is often used to enhance the safety of a water distribution system (WDS). While algorithms have been developed to select optimal water quality sensor placement strategies (WQSPS) for WDSs, many of them do not account for the influences caused by future uncertainties such as sensor failures and system changes (e.g., demand variations and configuration/expansion changes in the WDS). To this end, this paper proposes a comprehensive framework to evaluate the robustness of WQSPSs to these possible uncertainties. This is achieved by considering five different WQSPS's performance objectives as well as WDS's possible future demand and typology variations under a wide range of sensor failure scenarios. More specifically, an optimization problem is formulated to evaluate the robustness of the WQSPSs, where an evolutionary-based optimization approach coupled with an efficient data-archive method is used to solve this optimization problem. The framework is demonstrated on two real-world WDSs in China. The results obtained show that: (i) the WQSPS's robustness can be highly dependent on the performance objectives considered, implying that an appropriate objective needs to be carefully selected for each case driven by practical needs; (ii) the WDS's demand and configuration changes can have a significant influence on WQSPS's robustness, where the solution with more sensors in or close to the affected area is likely to better cope with these system changes; and (iii) the proposed framework enables critical sensors to be identified which can be then targeted for prioritizing maintenance actions.

Keywords

Water quality sensor placement strategy; Robustness; Water distribution system; Sensor failure

Introduction

Water distribution systems (WDSs) are vulnerable to contamination intrusion, including intentional contamination injections (Ostfeld et al., 2014) or accidental contamination intrusions (Perelman et al., 2012a). For instance, over a five-day period in October 2007, a boil-water notice was served on the majority of Oslo, Norway, as a result of a combination of bacteriological, Cryptosporidium oocysts and Giardia cysts found in the samples taken from the WDS (Robertson et al., 2008). More recently, a contamination event was reported in Hangzhou, China on 26 July 2020, where a sewer pipe was misconnected to a drinking water system in a small suburb (ChinaNews, 2020). Within the majority of the reported events, the contamination intrusion was detected by the residents through either the odor or color of the tap water in their properties, or public health issues diagnosed by the health professionals (He et al., 2018). This implies that the ability of water utilities in detecting water quality contamination events is limited, resulting in serious threats to water safety and public health (Rizak and Hrudey, 2008; Arad et al., 2013). Therefore, it is vital to develop an effective early contamination warning system (ECWS) for the WDS, aiming to detect and warn contamination intrusion events in a timely manner (Janke et al. 2006; Storey et al., 2011; Banik et al. 2017).

Water quality sensors could play an important role in the ECWS development, where the number of sensors and their spatial distributions can significantly affect the detection performance (Wu and Walski, 2006; Hart and Murray, 2010; Naserizade et al., 2018). Ideally, deploying a sensor at each node of the WDS can greatly improve the ECWS's detection ability, but this is generally not feasible due to limited budgets (Berry et al., 2005;

Ostfeld et al., 2008). In addition, some WDS nodes may also be unable to accommodate sensors because of topological and accessibility limitations. Consequently, studies have been carried out to optimally deploy a limited number of water quality sensors that are available and accessible in the WDSs, in order to maximize their effectiveness in detecting contamination events (Rathi and Gupta, 2015; Hu et al. 2017).

The optimization of the water quality sensor placement strategy (WQSPS) often needs to specify an objective function to maximize sensor system performance (Oliker and Ostfeld, 2014). Different objective functions have been proposed over the past few decades to enable WQSPS optimization. These include the detection time (Ostfeld and Salomons, 2004), the detection probability (Ostfeld et al., 2008), the affected population (Guidorzi et al., 2009), the consumption of contaminated water (Aral et al., 2010), the impacts of high-consequence events (Watson et al., 2009) and the network-wide observability of water quality indicators (Taha et al., 2021). In practice, it is difficult to use a single objective to identity a WQSPS that achieves the best performance in every aspect (Zhang et al., 2020a). Therefore, the selection of the appropriate objective function(s) is often a challenge that needs to account for the trade-offs among different performance metrics of the resultant WQSPSs (Ostfeld et al., 2008). In parallel to the development of different objective functions, various optimization algorithms have been proposed for WQSPS optimization. They include single and multi-objective optimization techniques (Kapelan et al 2003; Tinelli et al., 2018) as well as various advanced algorithms to improve optimization efficiency (Perelman and Ostfeld, 2012b; Tinelli et al., 2017).

In more recent years, research has been conducted to gain insights into the performance of

WQSPSs in monitoring and detecting WDS contamination events. For example, Zheng et al. (2018) have used distribution probability functions to reveal the characteristics of different WQSPSs in detecting contamination events. Subsequently, He et al. (2018) have accounted for the variation of contamination probabilities at different WDS nodes within the WQSPS optimization. It is found that the majority of previous studies have consistently assumed that all sensors can function perfectly over the entire design life. Such an assumption does not always apply to practical situations as failures of water quality sensors are not uncommon in WDSs (Berry et al., 2009; de Winter et al., 2019). These situations can be caused by internal structural failures, measurement errors, or communication failures (Berry et al., 2009). In recognizing the potentially high likelihood of sensor failures, attempts have been made to account for these situations in the design of WQSPSs (Preis and Ostfeld, 2008; Berry et al., 2009). More specifically, they aim to identify a WQSPS that cannot only perform well under normal conditions (perfectly working sensors), but also maintain its acceptable functionality levels during unexpected conditions that may lead to sensor failures (Mukherjee et al., 2017; Giudicianni et al., 2020).

More recently, Zhang et al. (2020a) have analyzed the WQSPS's performance variation as a result of a large range of sensor failure scenarios. Despite the merit of the work presented by Zhang et al. (2020a), their findings about WQSPS's detection performance are conditioned on a selected single objective function (i.e., the total contaminated water amount) and a fixed WDS structure. However, in practice, the WQSPS's performance should account for different aspects regarding water quality safety, in addition to the total contaminated water amount. In addition, the selection of the performance metric would also depend on the type of the contaminant and its transport/reaction dynamics in the WDS. More importantly, it is likely that the WDS's demand distribution and system topology can significantly vary within the design life of the water quality sensors. This is especially the case in many developing countries as a result of fast population growth and rapid urbanization (OECD, 2012).

Based on the review of the recent literature (Zhang et al., 2020a; Giudicianni et al., 2020), it can be concluded that while sensor failures have been increasingly considered within the WQSPS design process, the majority of the results are typically conditioned on a single performance metric and fixed WDS structures. In other words, the future uncertainties of the WDS (e.g., performance objective, demand and typology changes) have not been well accounted for during the selection of the WQSPSs. To this end, this paper proposes a new framework to evaluate the robustness of the WQSPSs under a wide range of uncertainty factors. These include different possible sensor failure scenarios, the use of different performance objectives and the possible future system changes to the WDS.

A few studies have considered various uncertainties within the WQSPS design process. For instance, Mukherjee et al. (2017) accounted for uncertainties induced by different demand patterns and various locations of contamination events. Giudicianni et al. (2020) handled the uncertainties related to the type of injected contaminant, source location, and intrusion time using the knowledge of the topology of the WDS. A recent study conducted by Taha et al. (2021) optimized network observability based on installed sensors under a range of uncertainties. These uncertainties include demand variations (different demand patterns for a given WDS), sensor noise, and hydraulic and water quality parameter changes over time.

However, Taha et al. (2021) did not account for sensor failures where no data is communicated for a period of time and WDS configuration changes (topology expansions for the WDS due to urbanization or population growth that can occur in future) that have been covered in our proposed methodology. Therefore, the present study significantly differs to the work stated in Taha et al. (2021). Regarding sensor failure, Taha et al. (2021) considered the noise within the measurements from sensors under a given variance. For such scenarios, signal processing methods can be used to deal with this data noise, thereby providing accurate parameter estimates. However, the current study considers the sensor failures where no data is communicated for a period of time. To handle such scenarios, it is necessary to identify a robust WQSPS to ensure the remaining sensors can provide a satisfactory detection performance.

The key contributions of this study are given as follows:

(i) This study attempts to analyze how the possible urbanization and the resulting WDS demand increases and configurational changes (e.g., network expansion) affect the robustness of the WQSPSs in ensuring water quality safety under sensor failures. Such an analysis offers insights into the underlying relationships between the WQSPS's robustness and WDS changes, thereby enabling the most robust WQSPS to be identified that accounts for future uncertainties.

(ii) A practically meaningful aspect of the present study is that it determines the relative importance of the water quality sensors in maintaining the WQSPS's detection performance based on the robustness values. This provides important guidance for the management and maintenance of water quality sensors that are deployed in WDSs.

The present study is a significant extension building on the work by Zhang et al. (2020a) in two main aspects. The main improvements include (i) the more comprehensive evaluation of the robustness of WQSPSs under possible sensor failures based on five different performance objectives as opposed to only one objective, and (ii) the former considers the impacts of the WDS configuration changes on the WQSPSs' robustness in dealing with sensor failures when no data is communicated for a period of time, but the latter is based on WDS without configuration changes (no demand changes and no network typology expansions).

Methodology

Define the robustness of the WQSPSs

Sensor failure scenarios

It is often difficult to ascertain the number of functioning sensors and which ones might fail within a given operating period (US-EPA, 2013; Spence et al, 2013). To address this issue, it is assumed that, for a given number of L failed sensors (denoted as the failure level L), all possible failure scenarios are considered and included in the robustness indicator of the WQSPS. Therefore, the number of failure scenarios, $k(L)$, can be mathematically described as $k(L) = C(TL, L)$, where C is the combination function and TL is the total number of sensors in the WQSPS. On this basis, the total number of failure scenarios K that considers all different L values can be expressed as $K = \sum_{L=1}^{TL} k(L)$.

Within the proposed robustness evaluation framework, the probability of each sensor failure level (i.e., the number of failed sensors) is identical, which may not conform to the real situations in many instances. For example, the failure probability of one or two sensors within a WQSPS is often greater than the probability associated with a large number of sensors simultaneously failing. Therefore, the robustness value expressed by the total of K failure scenarios accounts for the WQSPS's performance in dealing with the extreme case of many failed sensors. Such a particular situation is more often associated with natural disaster events such as urban floods or earthquakes (Zhang et al., 2020b). To address this problem in this study, we also analyze the robustness results for a relatively low L level (i.e., $L = 1$ or 2) in addition to the total K failure scenarios, to represent the system's typical situations regarding sensor failures.

Performance objectives

(i) Detection time

The detection time of a given WQSPS is described as follows (Ostfeld et al, 2008).

$$f_t = \frac{1}{M}\sum_{i=1}^{M} t_i \tag{1}$$

where f_t is the average detection time of all the total M intrusion events in the WDS; t_i is the detection time for the i^{th} intrusion event ($i = 1, 2, \ldots, M$). f_t only considers the detection time when the contamination event can be detected. For the undetectable events, their impacts will be assessed by the maximum retention time metric as shown below.

(ii) Detection probability

The detection probability of a WQSPS can be expressed as (Ostfeld et al, 2008)

$$f_p = \frac{1}{M}\sum_{i=1}^{M}\lambda_i \tag{2}$$

where f_p is the detection probability of the WQSPS across M contamination events; λ_i is an indicator function, with $\lambda_i = 1$ if the i^{th} contamination event is detected and 0 otherwise.

(iii) Consumed contaminated water

The consumed contaminated water performance objective can be described as (Hart et al., 2008; Zhang et al. 2020a)

$$f_w = \frac{1}{M}\sum_{i=1}^{M}V_i \tag{3}$$

$$V_i = \frac{\sum_{j=1}^{N} q_j(i)}{\sum_{j=1}^{N} DM_j(RT_i)} \tag{4}$$

where f_w is the performance objective function (in percentages) measured by the averaged consumed amount of polluted water over M contamination scenarios; V_i is the proportion of contaminated water that has been consumed relative to the total consumed water of the entire WDS for the WQSPS under the i^{th} intrusion event; $q_j(i)$ and $DM_j(RT_i)$ denote the total amount of contaminated water that has been consumed at node j (j =1, 2, …, N, N is the total number of nodes with demand users) and the total water demand required by node j, respectively, over the retention time of the i^{th} contamination in the WDS.

RT_i becomes t_i in Equation (1) for detectable contamination events. For undetectable events, $RT_i = t_i^e$, which is the elapsed time of all the contaminated water consumed during the undetected contamination event (i.e., the total retention time of the contaminant in the

WDS). The calculation of $q_j(i)$ is terminated once the intrusion event is detected by any of the sensors. The value of f_w is between 0 and 1, with a smaller value representing an overall better ability in mitigating the influence caused by contamination events. To measure the amount of polluted water, the result f_w is multiplied by the total amount of water within the entire simulation time to indicate the specific amount of water, in m^3.

(iv) Maximum retention time of the contamination in WDS

A set of extreme events, Ω, can be identified by performing a descending order based on the values of RT_i. Ω is used to represent a particular proportion of events (denoted as α) with the largest RT_i value. Consequently, the maximum retention time metric, f_r, can be defined as

$$f_r = \frac{1}{E_r} \sum_{e=1}^{E_r} RT_e, e \in \Omega \tag{5}$$

where E_r is the total number of events in the set of Ω, which equals to $\alpha_r \times M$. The f_t metric represents the average value for all detectable events, significantly differing from the f_r metric that is the average value for the contamination events with relatively long retention time in the WDS.

(v) Maximum number of potentially affected water users

For the i^{th} contamination event, the number of potentially affected water users of a given WQSPS can be expressed as (Ostfeld et al. 2008)

$$\mathrm{A}_i = \sum_{j=1}^{N} H_j(i) \times NP_j \tag{6}$$

$$NP_j = \frac{D_j}{\varphi} \tag{7}$$

$$H_j(i) = \Phi\left\{\beta \log_{10} \frac{q_j(i) \cdot c_j(i)}{W \cdot D_{50}}\right\} \tag{8}$$

where A_i is the number of potentially affected water users; $H_j(i)$ is the probability that a person would be infected or symptomatic due to the contaminated water at node j; NP_j is the total number of population associated with demand node j, which is estimated by the daily demands at node j (D_j) dividing by the daily average water consumption of each person (φ, liters/day/person)). The value of D_j can be computed based on the nodal demands in the WDS model.

The computation of $H_j(i)$ in Equation (8) follows the work of Chick et al. (2001, 2003), where Φ represents a standard normal cumulative distribution function; β and D_{50} are the Probit slope parameter (unitless) and dose that would result in a 0.5 probability of becoming infected or symptomatic (mg/kg), respectively; W is the assumed average body mass (kg/person); $q_j(i)$ is the total volume of the contaminated water that has been consumed by node j (liters), which is defined in Equation (4); $c_j(i)$ is the contamination concentration in the water consumed by node j (kg/L).

For a given WQSPS, A_i can be estimated using Equations (6-8), and the metric of the maximum number of potentially affected water users f_a is defined based on a ratio of α_a

events with the largest number of potentially affected water users, which is

$$f_a = \frac{1}{E_a}\sum_{e=1}^{E_a} A_e, e \in \Psi \tag{9}$$

where E_a is the total number of events in the set of Ψ, which equals to $\alpha_a \times M$. The f_w metric is the average consumed contaminated water for all contamination events, while the f_a metric is the average value for the contamination events with a relatively large affected population. In addition, the latter considers the contamination concentration at each demand node, but the former does not.

These performance objectives are selected due to their wide applications in literature and to account for performance assessment under normal (the first three) and extreme (the last two) scenarios based on their impact levels (e.g., retention time and affected population). While a different number of objectives can be used in engineering practice, it would not affect the application of the proposed methodology.

Robustness definition

In this study, the robustness is defined as the average value of a performance objective across K failure scenarios:

$$R(f) = \frac{1}{K}\sum_{k=1}^{K} f(k), f \in \{f_t, f_p, f_w, f_r, f_a\} \tag{10}$$

where $R(f)$ is the robustness value based on a particular performance objective f; k is the k^{th} sensor failure scenario. The metrics involved in Equation (10) can be simultaneously considered using a multi-objective framework, but this then brings a challenge of identifying the most robust WQSPS solution from a practical perspective. To this end, this study uses a traditional weight-based method to account for the impacts of different performance objectives. More specifically, we define a global robustness metric R as shown below.

$$R = \frac{1}{B}\sum_{b=1}^{B} rank_b(R(f)) \tag{11}$$

where $rank_b(R(f))$ is the rank of each performance objective f, with a smaller value representing a higher rank; B is the total number of performance objectives considered, where B=5 is used in this study. The R value represents the ranking of a certain WQSPS among all alternatives in robustness when measured by different performance objectives under a wide range of sensor failure scenarios. A smaller R value indicates that the WQSPS possess an overall better ability in maintaining its performance level when dealing with sensor failures measured by various performance objectives.

The problem formulation given in Equations (10) and (11) aims to identify the robust WQSPS that can have satisfactory detection performance even when sensor failures happen. For example, WQSPS A and B can have a similar performance if all sensors work well, each can show a significantly different performance if one or two sensors fail for these two WQSPSs. Therefore, the problem formulation in this study is practically meaningful as it can facilitate the selection of the robust WQSPS that can have satisfactory detection performance under sensor failures with no data sent for a long period of time.

Evaluate the robustness using a proposed optimization method

EA-based Approach for the robustness value evaluation

Equations (10) and (11) can be applied to a number of different WQSPSs, thereby determining the most robust WQSPS. However, the associated computational overheads can be massive due to that the total number of sensor failures K can be large for a real WQSPS. For example, if a WQSPS has 30 sensors, the total number of sensor failure scenarios is K=1.07×10^{9}. Conducting water quality simulations for such a large number of scenarios requires massive computational resources. To solve this issue, an evolutionary algorithm (EA) based optimization method is used in this study (Zhang et al. 2020a). While it is possible to use some traditional optimization techniques such as mixed integer programming (MIP) for this problem (Das and Dennis, 1997), the EAs are used in this study due to their flexibility in linking with hydraulic solvers (e.g., EPANET). However, future studies should explore the use of these traditional optimization techniques for solving this problem due to their merits in efficiency.

To enable the application of the EA, we first classify all the sensor failure scenarios into different groups based on the number of sensors failed. For example, if only one sensor fails, all the associated failure scenarios are assigned to the failure level L=1. Using this way, Equation (10) can be rewritten as

$$R(f) \approx \frac{1}{K_a}\sum_{L=1}^{TL} f(L), f \in \{f_t, f_p, f_w, f_r, f_a\} \tag{12}$$

$$K_a = \sum_{L=1}^{TL} k_a(L) \tag{13}$$

where $f(L)$ are the corresponding performance objective values for a selected f; $k_a(L)$ is the number of failure scenarios identified by the EA for L; the K_a is the total number of failure scenarios identified by the EA for all failure levels. Equations (12) and (13) are used to approximate the robustness value $R(f)$ using an EA, where the EA identifies a limited number of failure scenarios that can represent the distributions of all the possible failure scenarios for each L.

Based on Equations (12) and (13), the EA can be applied to identify the $f(L)$ for each particular failure level L with each performance objective considered. As such, a complex optimization problem that involves many sensor failure scenarios and many different objective performance objectives has been partitioned into a number of small-scale optimization problems that are computationally manageable. For a given S with a particular performance objective f, its maximization and minimization problems under the failure level L can be expressed as

$$f_{\max}(L) = \max\{f(L)\},\ \ f \in \{f_t, f_p, f_w, f_r, f_a\} \tag{14}$$

$$f_{\min}(L) = \min\{f(L)\},\ \ f \in \{f_t, f_p, f_w, f_r, f_a\} \tag{15}$$

where $f_{\max}(L)$ and $f_{\min}(L)$ are the maximum and minimum performance objective values respectively for a given sensor failure level L in a given WQSPS. Within the two optimization processes, the total number of identified failure scenarios is $k_a(L)$ in Equation (13) and their corresponding performance objective values are collected to form $f(L)$ in Equation (12).

To enhance the simulation efficiency of the proposed method, the data-archive method described in He et al. (2018) is adopted in this study. The principle of the data-archive method is to avoid the need for frequent calls to a water quality simulation model for EA function evaluations conditioned on a predefined set of contamination characteristics (e.g., intrusion concentration and duration). However, such an archive needs to be updated if the intrusion characteristics or WDS structures (e.g., demands or topology) are changed as these changes can affect the hydraulic parameters (e.g., velocity) and hence water quality simulation results (e.g., the contamination concentrations). More details of the data-archive method can be found in He et al. (2018).

Sensor importance assessment

As part of the proposed EA-based method, a particular sensor failure scenario can be identified with the minimum performance for each objective f under each failure level L (i.e., $f_{\min}(L)$ in equation (15). In other words, this particular sensor failure scenario can induce the largest consequences or threats to the WDS water quality safety. Therefore, the sensors within such a failure scenario need to be maintained better than other sensors with relatively small impact.

In this study, the frequency of each sensor failure that has been identified in the failure scenarios associated with the lowest performance objective values ($f_{\min}(L)$) over all different failure levels is calculated as follows

$$P_n(f) = \frac{1}{TL}\sum_{L=1}^{TL}\gamma(n, L, f) \qquad (16)$$

$$\gamma(n,L,f)=\begin{cases}1, & \text{sensor } n \text{ is included in the failure scenario associated with } f_{\min} \\ 0, & \text{otherwise}\end{cases} \tag{17}$$

where $P_n(f)$ is the frequency of sensor n that has been identified in the failure scenarios associated with the lowest robustness values ($f_{\min}$) over all different failure levels for a given performance objective f; $\gamma(n,L,f)$ = 1 if the sensor n is within the failure scenario that has the $f_{\min}$ value at the failure level L, otherwise $\gamma(n,L,f)$=0. A sensor with a higher value of $P_n(f)$ indicates more severe threats of its failure to the WDS water quality safety, thereby deserving more attention during the routine operation and management. To measure the sensor importance that jointly considers five performance objectives proposed in this study, a metric of P_n is defined as following.

$$P_n=\frac{1}{B}\sum_{b=1}^{B}P_n^b(f) \tag{18}$$

where P_n is the average frequency of sensor n, derived as the mean of the $P_n^b(f)$ over different performance objectives; B is the total number of performance objective considered (B=5 in this study). A higher P_n indicates that the sensor has a relatively important role in maintaining the performance of WQSPS under multiple objectives.

Impact of possible WDS variations on the robustness

It is critical to account for future system changes when determining the most robust WQSPS, which has not been done so far in literature. The impacts of the WDS's future uncertainties on the WQSPS's robustness can be expressed as

$$R_u(f) = R(f, \Lambda) \quad (19)$$

where $R_u(f)$ is the robustness value for a specific performance metric f under the future uncertainty conditions represented by Λ. In this study, Λ includes the demand variation and topology expansion as these two changes are common. Figure 1 illustrates the possible changes to the WDS, where (a) shows the nodes with increased demands (in blue) and (b) indicates the topology expansion of the WDS (in red). It is noted that the possible WDS variations are not directly incorporated in the robustness evaluation framework, but they can be considered as potential uncertainties that can affect the robustness of the WQSPSs.

Case studies

WQSPSs of two real-world WDSs

The proposed robustness evaluation method is applied to two real-world WDS case studies in China, the Jiayou Network (JYN) and the Zhuohao Network (ZHN). JYN consists of two supply reservoirs, 349 demand nodes and 509 pipes with different loops, as shown in Fig. 2, which provides an average water supply of 256,592 m^3 per day. Each reservoir provides an average of 50% water for the entire JYN, with respective water quality characteristics assumed to be identical. ZHN is composed of one reservoir, 3,439 demand nodes and 3,512 pipes with different branched and looped configurations (see Fig. 3), delivering an average of 140,782 m^3 water per day. The local water utilities plan to deploy 6 and 30 water quality sensors for the JYN and ZHN systems as stated in He et al. (2018), respectively, in order to build the water quality warning system.

He et al. (2018) has identified four different WQSPSs for these two WDSs, with results given in Figures 2 and 3. These WQSPSs are designed based on different nodal contamination probability functions adopted from He et al. (2018). More specifically, WQSPS1, WQSPS2, WQSPS3 and WQSPS4 are respectively conditioned on the equal contamination probability at each node, the probability function according to nodal demands, the probability function that considers the length of pipes immediately connected to the contaminated nodes and the probability function derived based on user properties. This study aims to evaluate the robustness of these four WQSPSs under sensor failures as well as to investigate the possible WDS changes to the robustness values. These results can facilitate the selection of the most robust sensor deployment methods that can satisfactorily deal with future uncertainties. It is noted that the details of the two WDSs, including the flow directions, the location of the reservoirs and pipe diameters, are submitted as the supplementary documents.

Settings of case studies

The EPANET2.0 was used as the hydraulic and water quality simulation model in this study (Rossman et al., 1994). A contamination scenario was represented by adding a contamination source to a network node with an injection rate of 100 mg/L of 2-h duration following the work of Ostfeld et al. (2008) and He et al. (2018). It was assumed that the contamination was injected to the WDS through a single demand node for each contamination event. Therefore, the total numbers of contamination scenarios for the JYN and ZHN cases were 24 (different injection times) $\times$ 349 (different injection nodes) = 8,376 and 24 $\times$ 3,439 = 82,536 respectively. All the parameters used in this study are outlined in

Table 1, where all the simulation related parameters were taken from He et al. (2018) and all the performance objective related coefficients were taken from Ostfeld et al. (2008) and Watson et al. (2009).

A few assumptions were made in the present study to enable water quality simulation. These include: (i) the contamination intrusion events are instantly detected if contamination concentration at any one of the sensors exceeds a threshold of 0.01mg/L (Table 1); and (ii) the contamination is conservative within the WDS (i.e., without decay during the entire event and the contaminant does not interact with disinfectants to any other chemicals in the water). These assumptions have been used in many previous studies (Ostfeld et al., 2008; Zheng et al., 2018). In this study, the sensor failure mode considered is the scenario of 'no data received over a period of time'. From an engineering perspective, water quality sensors can fail due to various external or internal factors, resulting in no data received over a period of time. This is a common situation in many water utilities, and fixing such sensors often requires some time due to many of them requiring the involvement of external contractors to fix the fault. Therefore, this particular scenario, when a number of sensors do not record/communicate data over a prolonged period of time due to their failure, is a realistic situation in many WDSs. This is different from the scenario when a sensor sends data that is corrupted or erroneous. Considering the former type of sensor failures within the WQSPS design process is necessary as it not only ensures the system's high detection performance when all sensors work well, but also can provide satisfactory performance under sensor failure scenarios.

While signal processing methods may be used during the operational stage to analyze the data from sensors, they have to be conditioned on the data availability, which is the not the sensor failure scenario considered in the present study. The f_a metric is a function of the contaminant concentration at WDS nodes, which is influenced by the contamination injection rate. Therefore, the f_a results in this study are conditioned on the used contamination injection rates given in Table 1, but the proposed methodology can be used for other rates.

While different EAs are available, Borg (Hadka and Reed, 2013; Zheng et al., 2016) was adopted in this study as it has been successfully used to deal with various water resources optimization problems. The population size of Borg applied to JYN and ZHN case studies were 500 and 1000 respectively following the parameters used in He et al. (2018), and the maximum allowable number of evaluations was 500,000 for both case studies. For other Borg parameters, the default values were used as they have been demonstrated to show satisfactory searching performance (Hadka and Reed, 2013)

Possible system variations of the two WDSs

For the two case studies, the nodal demands at a particular region within the WDS were increased to explore their impacts on the robustness values. More specifically, for the JYN case study, water demands of 29 nodes in the area closed by the blue line in Fig. 4(a) were increased by 50%. For the ZHN case study, water demands of 304 nodes in the area closed by the blue line in Fig. 4(b) were increased by 100%. These possible demand-increase scenarios were adopted as a result of the consultation with the local water utility, which were based on that the population density of these two regions can significantly increase in future. In terms of typology changes, 8 nodes and 17 pipes were added to the right side of the JYN system as shown in Fig. 4(c), and 77 nodes and 91 pipes were added to the left side of the ZHN system as shown in Fig. 4(d). Water demands of 10L/s and 0.3L/s were used for the newly added nodes for the JYN and ZHN cases, respectively. These two possible topology change scenarios were also provided by the local water utility, which were based on the future planning strategies of the cities.

It is noted that the increasing demand scenarios are considered in this study due to the two case studies being from China where the population is growing. However, demand reductions are also possible especially in highly developed countries due to the rise in the adoption of water conservation practices and efficient water use appliances (Davies, 2014; Dieu-Hang, 2017; Stavenhagen, 2018). For such demand change scenarios, the resultant impacts on the WQSPS's robustness can be assessed in a straightforward manner using the proposed method.

Results and discussion

Robustness analysis of WQSPSs

Robustness values versus failure levels

Fig. 5 present the robustness values defined in Equation (12) of five performance objectives under different sensor failure levels, i.e., $L = 0$ (no sensor fails), $L = \{1, 2\}$, and $L = \{1, 2, \ldots, TL\text{-}1\}$). As expected, it can be observed that the performance of each WQSPS was deteriorated as measured by the five objectives when the sensor failure level L increased. For instance, the average detection time of the WQSPS1 for the JYN case study can increased from 0.86 hours when all sensor function properly (L=0) to 1.21 hours if the sensor failure level was L= $\{1, 2, \ldots, TL\text{-}1\}$ as shown in Fig. 5(a). Similarly, the number of affected people

($R(f_a)$ value) under the extreme contamination events of the ZHN case study with the WQSPS2 (L=0) was around 1.45×10^4, and this value moderately increased to 2.04×10^4 when L={1, 2}, but followed by a sharp increase up to 4.97×10^4 for L= {1, 2, …, TL-1}. Similar observations can be made for other performance objectives and WQSPSs.

It is also observed that the WQSPS's performance's decline can vary at a different rate over different failure levels. For instance, the $R(f_t)$ value of the WQSPS4 (Fig. 5(b)) for the ZHN case study increased from 3.33 hours to 3.56 hours due to a low level of sensor failures (L={1, 2}), but followed by a significant increase up to 16.85 h when L increased to {1, 2, …, TL-1}. This indicates that the WQSPS4 required a rather long average time to detect the contamination events when many sensors failed. This is because the WQSPS4 possessed a relatively larger detection probability (Fig. 5(d)) compared to other WQSPSs, and hence the corresponding mean time for these detectable contamination events was relatively large as a result of a significant number of failed sensors. Another interesting observation was that the $R(f_r)$ values of different WQSPSs consistently remained almost constant over different sensor failure levels (Fig. 5(g, h)). This is because the performance objective f_r focused on the impacts of the extreme contamination events, and many of these events were not detectable due to the low number of sensors for the two WDSs. Consequently, the contamination events associated with the f_r were overall similar over different WQSPSs at various failure levels, leading to a similar f_r value as shown in Fig.5(g, h).

Results in this subsection imply that water quality sensor failures can significantly deteriorate the WQSPS's detection performance, with a large failure level (i.e., a larger number of sensors failed) indicating a greater performance reduction. Therefore, accounting for the uncertainty caused by sensor failures within the WQSPS design is highly necessary to enable the water quality safety of the WDSs.

Robustness ranks versus different performance objectives

Tables 2 and 3 show the robustness results (ranking values) of the WQSPSs for the two case studies based on each of the five performance objectives (Equation 10) as well as all the performance objectives considered (Equation 11). For the JYN case study, if all the sensors work properly (L=0), the sensor design solutions with the best performance (the first ranking) based on $R(f_t)$, $R(f_p)$, $R(f_w)$, $R(f_r)$, $R(f_a)$ were WQSPS3, WQSPS4, WQSPS4, WQSPS1 & WQSPS4, and WQSPS1 respectively as shown in Table 2. When considering all the possible sensor failure scenarios (L={1, 2,…, TL-1}), the most robust design solutions based on $R(f_t)$, $R(f_p)$, $R(f_w)$, $R(f_r)$, $R(f_a)$ were WQSPS3, WQSPS2, WQSPS1 & WQSPS4, WQSPS4, WQSPS1. This shows that the robustness performance of a WQSPS is not only affected by various failure levels, but also significantly influenced by the use of different performance objectives. Similar observations can be made for the ZHN case study as shown in Table 3. This highlights the great necessity to select an appropriate performance objective for a given case based on the practical need as well as the importance to simultaneously account for multiple objectives when determining the most robust WQSPSs.

In terms of R value that considers all the five performance objectives, the WQSPS1 and WQSPS4 overall performed the best for the JYN case study. This was supported by the fact that these two design strategies always had relatively low ranking values (better performance) over different failure levels (Table 2). For the ZHN case study, the most robust design solution was the WQSPS4 due to its relatively high ranks over different sensor failure levels when considering all the five design objectives (Table 3). The WQSPS4 was designed based on assigning more sensors to important users as did in He et al. (2018). Consequently, the WQSPS4 tended to have a better performance in detecting extreme contamination events which were often associated with important water users (e.g, large water users at highly commercially areas) compared to other sensor design strategies. This accordingly led to its relatively high performance when measured by the objectives of f_r and f_a which focused on the extreme impacts of the contamination events.

Robustness analysis that considers the WDS changes

The proposed framework was applied to evaluate the robustness ranking values (i.e., R) of the WDS with demand and topology changes. As shown in Figs. 6(a, c), when the nodal demands increased in the particular area of the JYN case study (Figure 4(a)), the R ranking value of the WQSPS3 changed significantly. This is proved by the observations that the WQSPS3 exhibited the low performance for the original JYN case study for both $L = \{1, 2\}$ and $L = \{1, 2, \ldots, TL\text{-}1\}$, but it showed the best detection performance (the lowest ranking value) for the given demand increase scenario. This is mainly because two sensors of the WQSPS3 (Fig. 2(c)) were located within the area with demand increases (Fig. 4(a)), and hence its detection performance can maintain a relatively high level. Interestingly, when the network's topology expanded as shown in Figure 4(c) for the JYN case study, the WQSPS3 turned out to have the worst performance. For this WDS change scenario, the WQSPS2 that had the overall low performance for the original JYN consistently showed the best detection ability as shown in Figure 6(a, c). This is due to that the WQSPS2 had a larger number of sensors located in the surrounding region of the newly added pipes of the JYN case study compared to other design alternatives.

For the ZHN case study, the WQSPS2 consistently exhibited improved robustness in detection performance for both demand and topology change scenarios (Fig. 6(b, d)) relative to the original WDS. However, the WQSPS1 showed a significantly reduced robustness performance under these two WDS variations. This can be explained by the fact that the number of sensors of the WQSPS2 located in the WDS region with demand and topology changes was significantly higher than the WQSPS1 as shown in Figure 4. It is also noted that the rank changes are different for the two case studies. For the JYN case study under L= {1, 2}, WQSPS2 changes from the worst to the best ranked when the system topology is changed. However, this rank change is relatively moderate for the ZHN case study (e.g., WQSPS3 changes from the worst to the second worst, Figure 6(b)). This is due to the fact that JYN is a small-size transmission network with a highly looped structure and large pipe diameters and hence the demand increase/topology changes can result in large impacts on its hydraulic properties (e.g., velocities). In contrast, since the ZHN is a large distribution network with relatively small diameters, the system changes cannot induce large hydraulic impacts and hence the rank variation of the WQSPSs is moderate. Results in this subsection imply that the WDS's demand and topology changes can significantly affect the robustness performance of the WQSPSs under sensor failures. Deploying more sensors close to the area with potentially increasing demands or topology expansion is effective to ensure a relatively high and robust detection performance of the WQSPSs under future uncertainties (e.g., sensor failures).

Sensor importance assessment

Sensor importance assessment versus different performance objectives

The sensor importance assessment was conducted to identify the critical sensors in the WQSPS with different performance objectives using the $P_n(f)$ defined in Equation (16). While the $P_n(f)$ values have been calculated for all different WQSPSs, $P_n(f)$ values for the WQSPS3 of the JYN case study and the WQSPS2 of the ZHN case study were only presented in Tables 4 and 5 for illustration. These two sensor design solutions were selected due to their overall more significant changes in robustness values relative to other alternatives in handling future uncertainties (demand increase and topology changes). In addition, to enable clear presentation, only the most important two and three sensors were given for $L = \{1, 2\}$ and $L = \{1, 2, \ldots, TL\text{-}1\}$ respectively in these two tables.

As shown in Table 4, for $L = \{1, 2\}$, the two most important sensors that their failures can significantly reduce the WQSPS's detection performance when measured by the performance objectives of f_t, f_p, f_w f_r and f_a are {6, 2}, {4, 5}, {4, 5}, {1, 4} and {1, 5} respectively, with index number given in Figure 2(c). When all different failure scenarios were considered ($L = \{1, 2, \ldots, TL\text{-}1\}$), the three most important sensors were also varied among different performance objectives. For instance, the sensor 6 is ranked to be the first when measured by f_t, but it changed to the sensor 1 when evaluated by f_r. For the ZHN case study in Table 5, the most important senor based on the f_t, f_p f_w f_r and f_a are 7, 16, 16, 1 and 1 respectively for both $L = \{1, 2\}$ and $L = \{1, 2, \ldots, TL\text{-}1\}$.

Results in this subsection imply that the importance of the sensors can be a function of varying performance objectives. This highlights the great necessity of accounting for multiple performance objectives in order to not only identify the most robust design solutions, but also to understand the importance of sensors. Such insightful knowledge can provide engineering guidance for sensor maintenance, where more resources (e.g., repair, routine check) should be assigned to important sensors as their failures can significantly reduce the WQSPS's detection performance.

Impacts of WDS changes on sensor importance

We computed the average ranks for each sensor across different performance objectives for the original WDS as well as the WDS with demand and topology changes. Results for the WQSPS3 of the JYN case study and the WQSPS2 of the ZHN case study were used for illustration (Tables 6 and 7), where the two and three most important sensors were presented for $L = \{1, 2\}$ and $L = \{1, 2, \ldots, TL\text{-}1\}$ respectively.

As shown in Table 6, for $L = \{1, 2\}$, the two most important sensors varied for the JYN case study when the WDS's demand and topology changed (Figure 4). For instance, the sensors {4, 6} are critical to ensure the WQSPS3's performance for the original WDS, but they were changed to {3, 5} and {6, 1} respectively when the future demand and topology variation scenarios were accounted for. Similar observations can be made for $L = \{1, 2, \ldots, TL\text{-}1\}$. In contrast, the sensor rankings for the WQSPS2 were not significantly varied when the ZHN's demand and topology changed. For example, the sensor 1 was consistently selected as the most important sensor across the two different system change scenarios under various failure levels.

We also note that the variation of the senor's importance for the JYN case study under system changes is overall larger than that of the ZHN case study. This can be attributed to two main factors: (i) the number of sensors in the JYN case study is lower due to its small network scale; and (ii) the hydraulic properties of the JYN case study changed more significantly than ZHN due to its highly looped structure. Results in this subsection showed that while the system changes of the JYN case study can significantly influence the sensor ranking values, but the ZHN did not exhibit a similar phenomenon. This indicates that the impact of the system changes on the sensor rankings can be complex as it can be also affected by the network properties (spatial scale, flow direction and so on). This implies that a detailed analysis using the proposed framework is necessary to comprehensively understand the relative importance of different sensors in the WQSPSs.

Conclusions

This paper proposed a comprehensive framework to evaluate the robustness of the WQSPSs under a range of uncertainties, including sensor failures, the use of different objectives to represent the WQSPS's detection performance and the WDSs changes. Two real-world WDSs with four WQSPSs for each WDS analyzed were used to demonstrate the utility of the proposed framework. Based on the application results and analysis, the main conclusions and practical implications can be summarized as follow:

(i) The robustness of the WQSPSs in dealing with future uncertainties (sensor failures) was dependent on the performance objectives used. This implies that an appropriate objective needs to be carefully selected for each case driven by practical needs, as well as that multiple objectives needs to simultaneously considered in order to comprehensively assess the WQSPS’s robustness.

(ii) Significant impacts of the WDS changes (network expansion and demand increase) on the robustness of WQSPSs were found in both case studies. The results showed that the WQSPS with more sensors in or close to the changed areas had relatively higher robustness in coping with these variations. This insight not only highlights the importance to account for future changes to the WDS within the WQSPS design process, but also facilitates the selection of the most WQSPSs for WDSs in dealing with future uncertainties.

The framework proposed enables critical sensors to be identified, based on the sensor importance assessment at different sensor failure levels. The results demonstrated that the crucial sensors varied across different objectives and WDS modifications. In general, the importance of sensors, which in or close to the changed areas, would increase after WDS changes. This knowledge about the importance and priority of sensor maintenance can provide guidance to enable efficient and effective water quality sensor management in WDSs.

Based on the results of the two case studies, the following recommendation can be made. For the relatively low failure levels with one or two sensors failed (i.e., $L=\{1, 2\}$), which is highly likely in engineering practice, WQSPS4 can be the most robust solution for both the original JYN and ZHN case studies under the joint consideration of the five performance objectives. However, for the given demand increase and topology change scenarios for the JYN case study (Figure 4), the WQSPS3 and WQSPS2 exhibited the most robust performance respectively. For the ZHN case study, the WQSPS2 consistently performed the best under different scenarios with system changes. These observations can be practically meaningful as they can assist the local water utilities to identify the most robust WQSPSs for the two case studies considered.

In this study, we assessed the robustness of the four WQSPSs for a wide range of future uncertainties including sensor failures and system changes. While it is theoretically possible to add this robustness criterion as an objective within the WQSPS design optimization process, it can be challenging due to the additional computational overhead. However, future work should incorporate the proposed methodology into the WQSPS design process with further consideration paid to computational efficiency.

Data Availability

All data, models (INP files), or codes that support the findings of this study are available from the corresponding author upon reasonable request.

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Table 1 Parameter settings for the two case studies

Categories	Meanings	Parameters	Values
Simulation related parameters	Total simulation time	-	96 h
	Number of demand patterns	-	24
	Time step	-	5 min
	Contamination source injection rate	-	100 mg/L
	Contamination source injection duration	-	2 h
	Detection threshold of water quality sensors	-	0.01 mg/L
Performance objective related parameters	Percentage of extreme events of $f_r(S)$	α_r	0.5%
	Percentage of extreme events of $f_a(S)$	α_a	0.5%
	Total per capita water demand rate	φ	300 L/day/person
	Probit slope parameter	β	0.34 (-)
	Dose with a 0.5 probability of being infected or symptomatic	D_{50}	41 mg/kg
	Assumed average body mass	W	70 kg

Table 2 The robustness rankings of the WQSPSs of the JYN

L levels	$L = 0$				$L = \{1, 2\}$				$L = \{1, 2, \ldots, TL\text{-}1\}$			
WQSPS	1	2	3	4	1	2	3	4	1	2	3	4
$rank(R(f_t))$	2.0	3.0	1.0	4.0	2.0	2.0	2.0	4.0	3.0	2.0	1.8	3.2
$rank(R(f_p))$	2.0	3.0	4.0	1.0	2.5	2.5	4.0	1.0	2.4	1.6	3.8	2.2
$rank(R(f_w))$	2.0	4.0	3.0	1.0	2.0	4.0	3.0	1.0	2.0	2.4	3.6	2.0
$rank(R(f_r))$	1.0	3.0	3.0	1.0	1.5	4.0	3.0	1.0	1.2	3.4	3.0	1.0
$rank(R(f_a))$	1.0	2.0	2.0	4.0	2.0	4.0	2.0	2.0	1.6	2.2	2.0	2.2
R	1.6	3.0	2.6	2.2	2.0	3.3	2.8	1.8	2.0	2.3	2.8	2.1

Table 3 The robustness ranks of the WQSPSs of the ZHN

L levels	$L = 0$				$L = \{1, 2\}$				$L = \{1, 2, \ldots, TL\text{-}1\}$			
WQSPS	1	2	3	4	1	2	3	4	1	2	3	4
$rank(R(f_t))$	1.0	3.0	2.0	4.0	1.0	3.0	2.0	4.0	1.8	3.0	1.2	4.0
$rank(R(f_p))$	4.0	2.0	3.0	1.0	3.0	2.0	4.0	1.0	2.7	2.3	4.0	1.0
$rank(R(f_w))$	3.0	1.0	4.0	2.0	3.0	1.0	4.0	2.0	1.5	1.6	3.9	3.0
$rank(R(f_r))$	2.0	3.0	4.0	1.0	2.0	3.0	4.0	1.0	2.0	3.0	4.0	1.0
$rank(R(f_a))$	4.0	1.0	3.0	2.0	4.0	1.5	3.0	1.5	2.9	1.6	2.9	2.5
R	2.8	2.0	3.2	2.0	2.6	2.1	3.4	1.9	2.2	2.3	3.2	2.3

Table 4 The sensor importance assessment of the WQSPS3 of the JYN

L levels	Objectives	Identified important sensors (Sensor index ($P_n(f)$))		
$L = \{1, 2\}$	f_t	6 (100%)	2 (50%)	
	f_p	4 (50%)	5 (50%)	
	f_w	4 (50%)	5 (50%)	
	f_r	1 (100%)	4 (50%)	
	f_a	1 (50%)	5 (50%)	
$L = \{1, 2, \ldots, TL\text{-}1\}$	f_t	6 (83.3%)	2 (83.3%)	1 (66.7%)
	f_p	4 (83.3%)	5 (83.3%)	6 (83.3%)
	f_w	4 (83.3%)	5 (83.3%)	6 (83.3%)
	f_r	1 (100%)	2 (66.7%)	3 (66.7%)
	f_a	4 (83.3%)	5 (83.3%)	6 (83.3%)

Table 5 The sensor importance assessment of the WQSPS2 of the ZHN

L levels	Objectives	Identified important sensors (Sensor index ($P_n(f)$))		
L = {1, 2}	f_t	7 (100%)	5 (50%)	
	f_p	16 (100%)	1 (50%)	
	f_w	16 (100%)	1 (50%)	
	f_r	1 (100%)	25 (50%)	
	f_a	1 (100%)	16 (50%)	
L = {1, 2, …, TL-1}	f_t	7 (100%)	5 (96.7%)	2 (93.3%)
	f_p	16 (100%)	1 (96.7%)	7 (93.3%)
	f_w	16 (100%)	1 (96.7%)	7 (93.3%)
	f_r	1 (100%)	6 (67.7%)	18 (63.3%)
	f_a	1 (100%)	10 (90%)	11 (90%)

Table 6 The sensor importance assessment of the WQSPS3 for the JYN case study under demand and topology variations

L levels	JYN case study	Identified crucial sensors (Sensor index (P_n))		
L = {1, 2}	Original	4 (40%)	6 (40%)	
	Demand increase	3 (40%)	5 (40%)	
	Topology change	6 (50%)	1 (40%)	
L = {1, 2, …, TL-1}	Original	4 (73.3%)	6 (73.3%)	1 (63.3%)
	Demand increase	3 (66.7%)	1 (63.3%)	4 (60%)
	Topology change	6 (83.3%)	5 (76.7%)	1 (63.3%)

Table 7 The sensor importance assessment of the WQSPS2 for the ZHN case study under demand and topology variations

L levels	ZHN case study	Identified crucial sensors (Sensor index (P_n))		
$L = \{1, 2\}$	Original	1 (60%)	16 (50%)	
	Demand increase	1 (90%)	25 (30%)	
	Topology change	1 (60%)	16 (50%)	
$L = \{1, 2, \ldots, TL\text{-}1\}$	Original	1 (96%)	5 (81.3%)	7 (78%)
	Demand increase	1 (98.7%)	7(79.3%)	5 (77.3%)
	Topology change	1 (94.7%)	5 (81.3%)	7 (80%)

Figure captions

Figure 1 The schematic diagram of the WDS variations: (a) Water demand increase; (b) System topology change

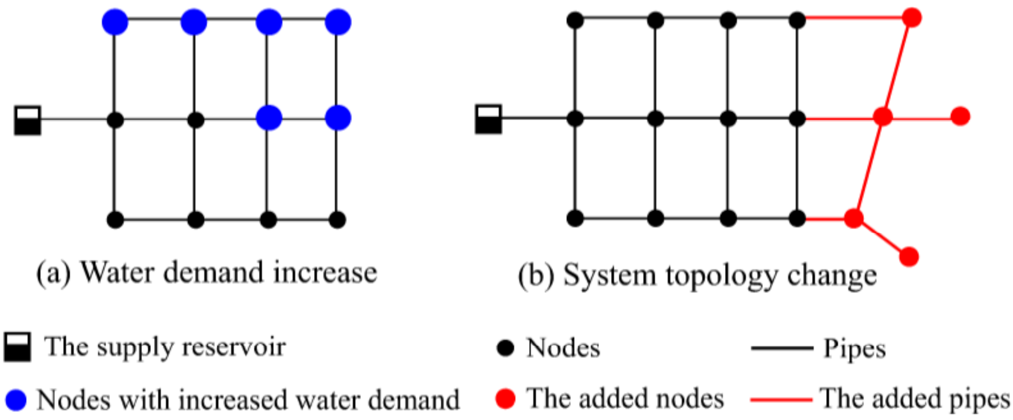
Figure 2 The four WQSPSs of the JYN case study, where the number indicates the sensor index: (a) WQSPS1; (b) WQSPS2; (c) WQSPS3; (d) WQSPS4

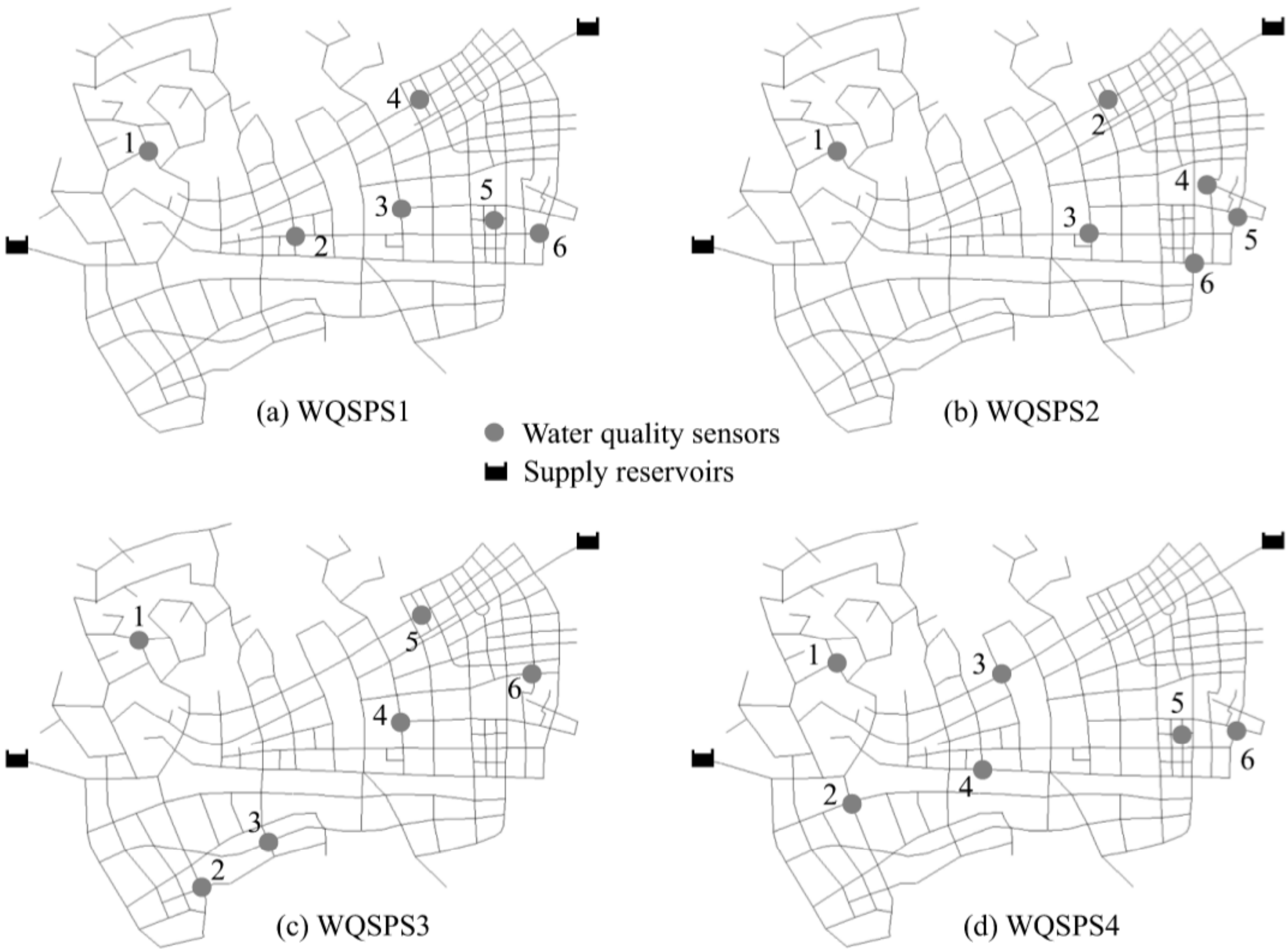
Figure 3 The four WQSPSs of the ZHN case study, where the number indicates the sensor index: (a) WQSPS1; (b) WQSPS2; (c) WQSPS3; (d) WQSPS4

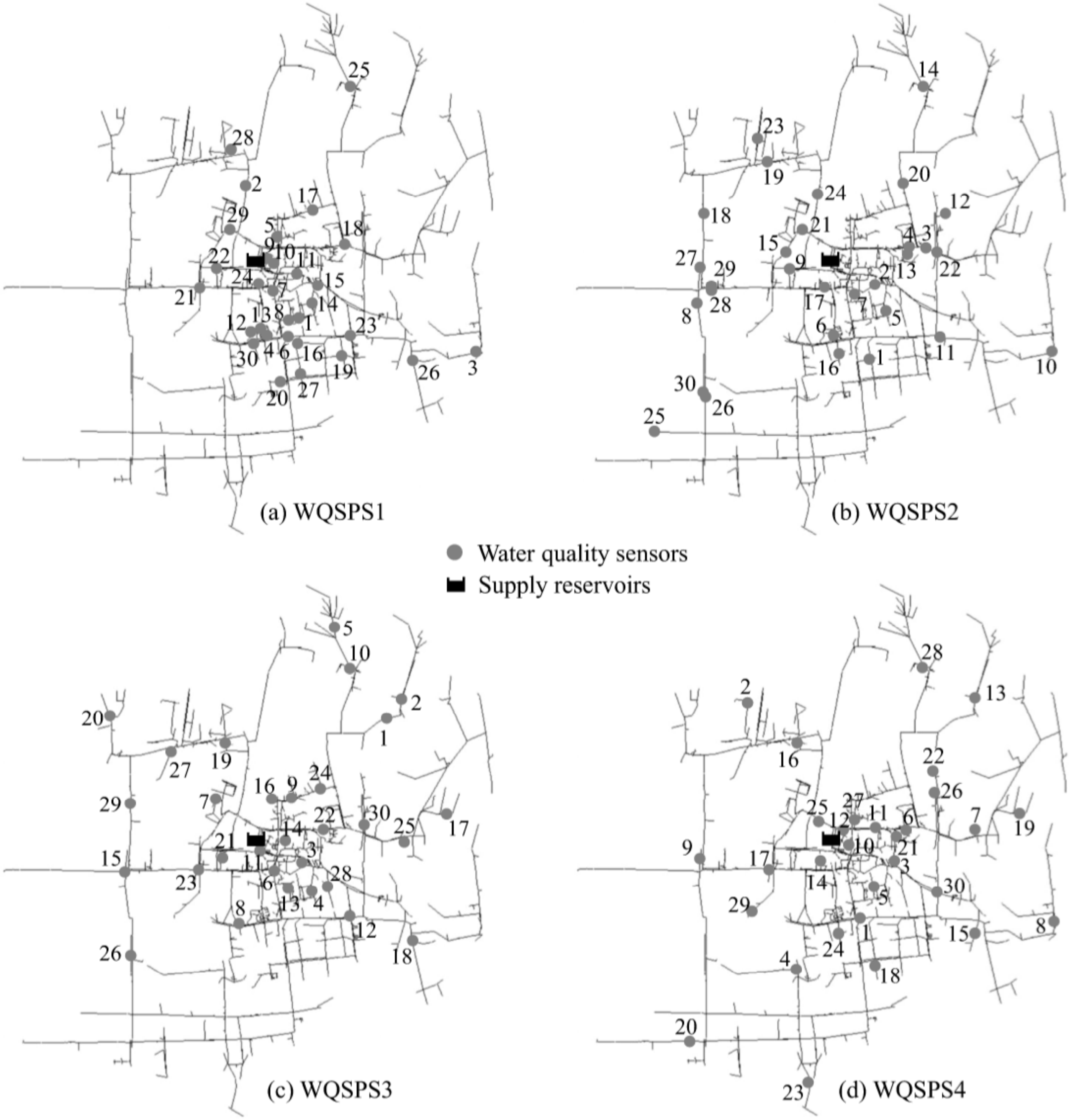
Figure 4 Structure variations of the two case studies: (a) and (b) are JYN and ZHN respectively with increased nodal demands in the area closed by the blue line; (c) and (d) are JYN and ZHN respectively with changed system topology represented by red nodes and lines

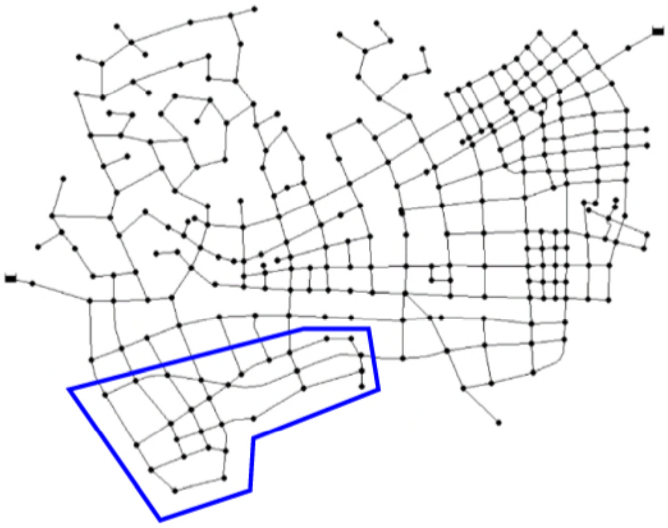
Figure 5 Robustness values of the four WQSPSs for the two case studies: (a)JYN; (b) ZHN; (c)JYN; (d) ZHN; (e)JYN; (f) ZHN; (g)JYN; (h) ZHN; (i)JYN; (j) ZHN

Figure 6 Robustness ranks (*R* values) of the four WQSPSs for the two case studies considering demand and topology changes: (a) and (b) $L = \{1, 2\}$; (c) and (d) $L = \{1, 2, \ldots, TL\text{-}1\}$

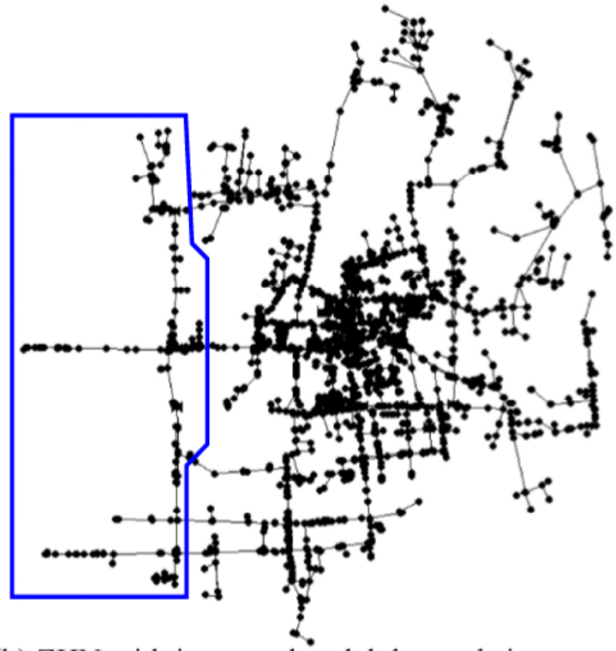

(a) Water demand increase
(b) System topology change
The supply reservoir
Nodes with increased water demand
Nodes
The added nodes
Pipes
The added pipes


(a) WQSPS1
(b) WQSPS2
Water quality sensors
Supply reservoirs
(c) WQSPS3
(d) WQSPS4

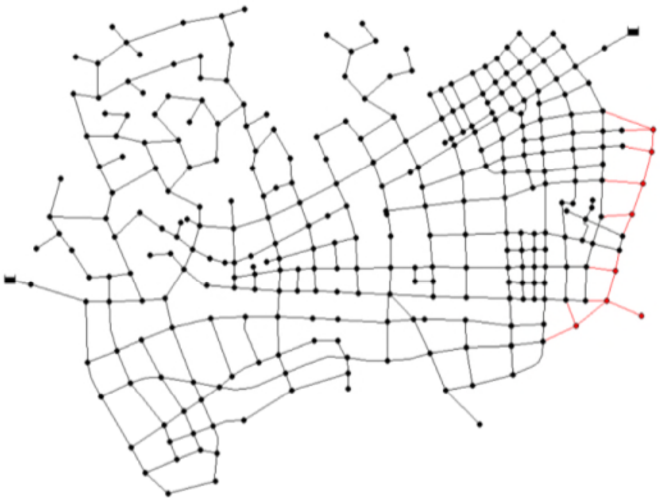

(a) WQSPS1
(b) WQSPS2
Water quality sensors
Supply reservoirs
(c) WQSPS3
(d) WQSPS4



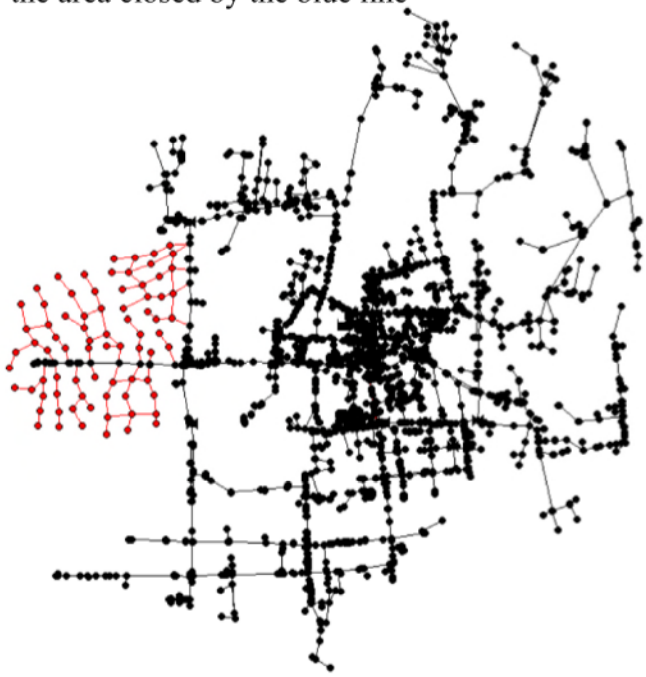
(a) JYN with increased nodal demands in the area closed by the blue line



(b) ZHN with increased nodal demands in the area closed by the blue line



(c) JYN with changed system topology represented by red nodes and lines



(d) ZHN with changed system topology represented by red nodes and lines

Figure 5

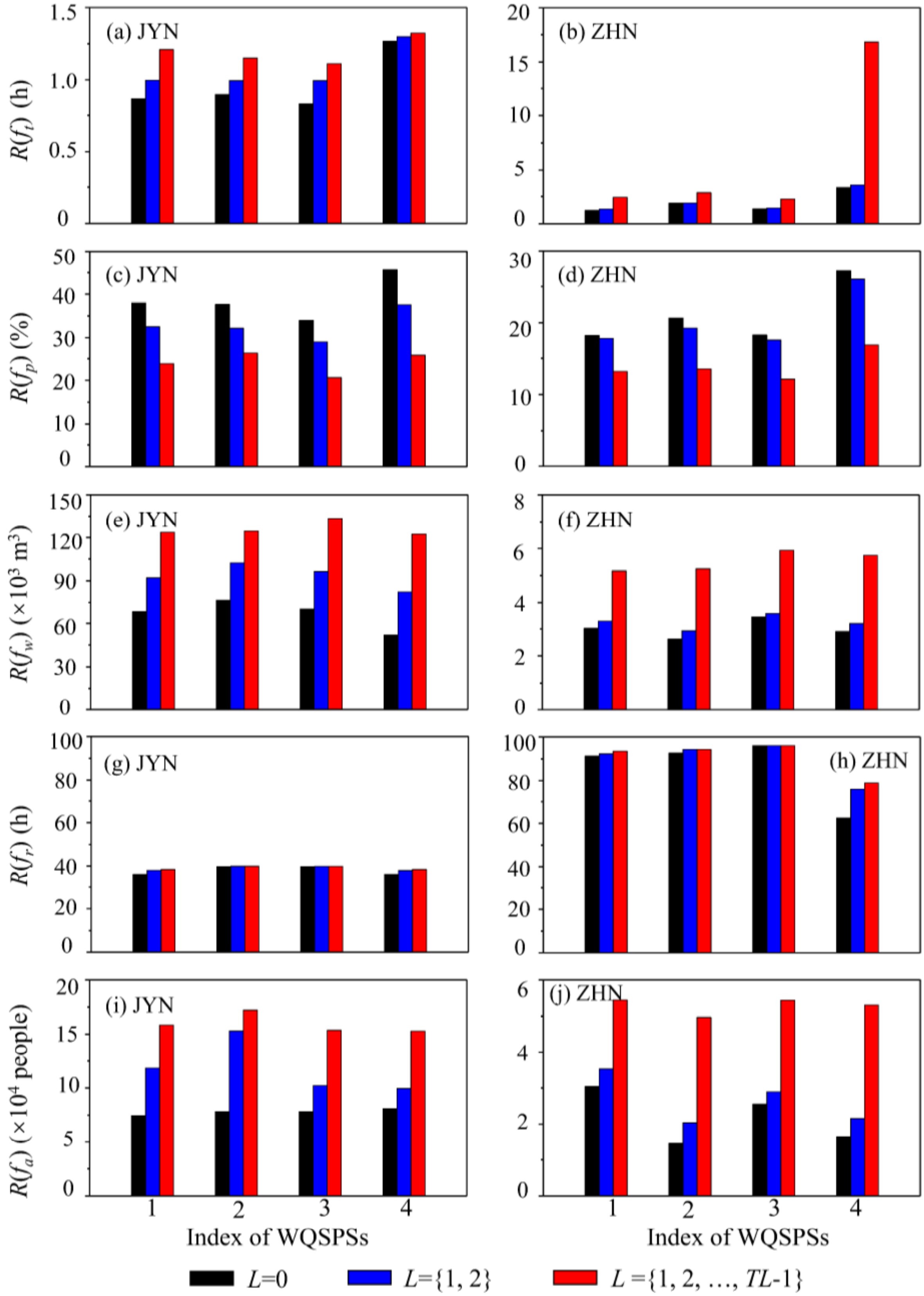
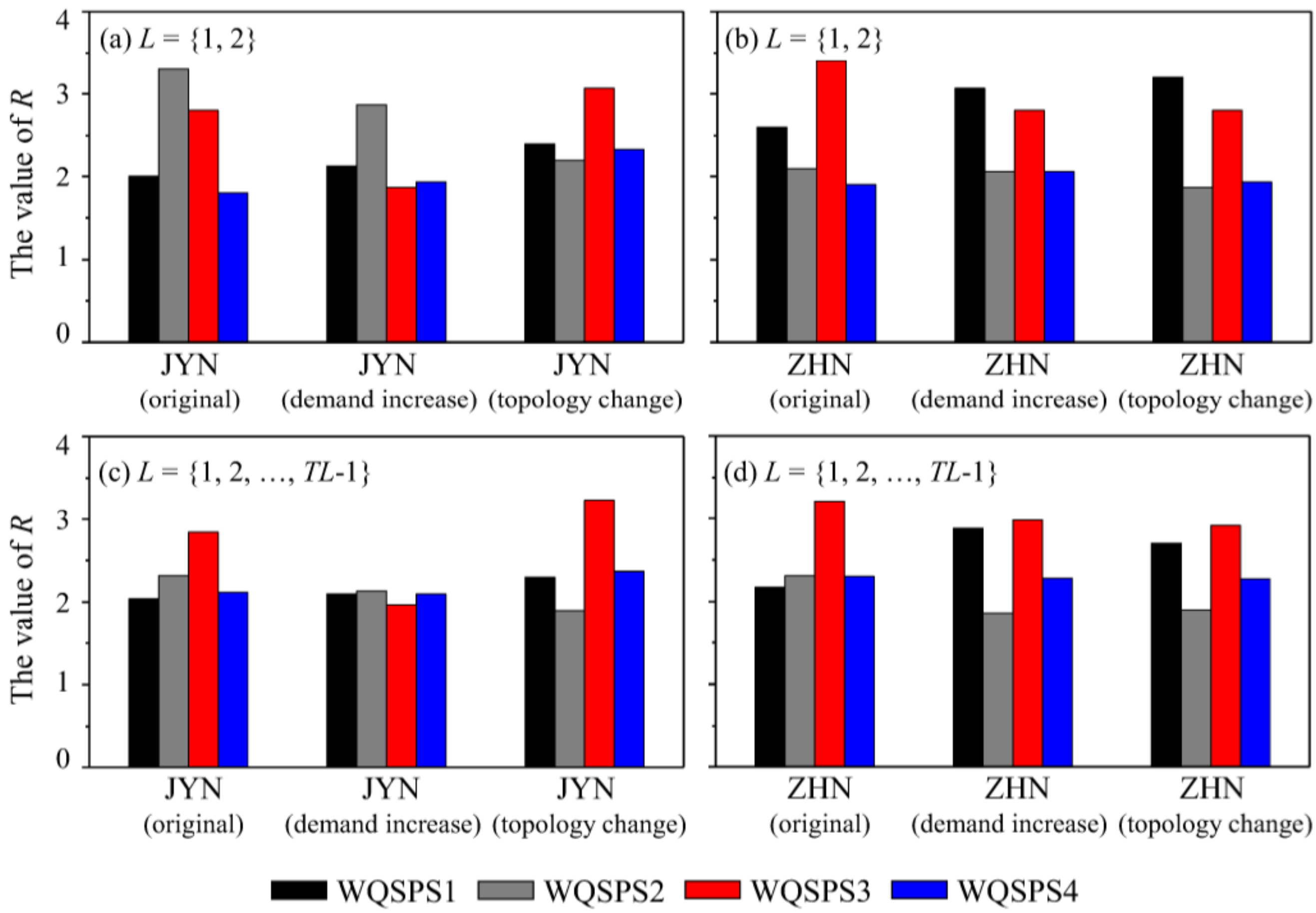

(a) JYN
(b) ZHN
(c) JYN
(d) ZHN
(e) JYN
(f) ZHN
(g) JYN
(h) ZHN
(i) JYN
(j) ZHN
$R(f_t)$ (h)
$R(f_p)$ (%)
$R(f_w)$ ($\times 10^3$ m^3)
$R(f_r)$ (h)
$R(f_a)$ ($\times 10^4$ people)
Index of WQSPSs
L=0
L={1, 2}
L ={1, 2, …, TL-1}

Figure 6



(a) L = {1, 2}
(b) L = {1, 2}
(c) L = {1, 2, …, TL-1}
(d) L = {1, 2, …, TL-1}
The value of R
0
1
2
3
4
JYN (original)
JYN (demand increase)
JYN (topology change)
ZHN (original)
ZHN (demand increase)
ZHN (topology change)
WQSPS1
WQSPS2
WQSPS3
WQSPS4