Optimal model of desalination planning under uncertainties in a water supply system

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1 **Optimal model of desalination planning under uncertainties in a water supply system**

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7 **Abstract.**

8 A requirement for developing desalination in coastal regions suffering water scarcity is proposed to address
9 the increased water demand and limited traditional water supply. The determination of plant capacity and
10 water allocation scheme in a multiple-source water supply system, the first problem in planning desalination
11 under stream flow and water demand uncertainties, remains a challenge. To address this gap, an interval-
12 parameter two-stage stochastic programming model is developed in this study. The first-stage problem is to
13 determine a proper desalination plant capacity, and the second is the water allocation scheme under
14 uncertainties of natural stream flows, water demands, benefits and economic losses. The objective function is
15 to maximize the net benefit of the system, and the cost function of desalination, including capital and
16 operational costs, implying environmental impact, is linearized within a range of plant capacities to solve the
17 model. The proposed approach is applied to an urban area of Weihai city in China to illustrate the validity of
18 the model. The results suggest a capacity of $46 \times 10^3 \text{ m}^3/\text{d}$ in 2030 and $56 \times 10^3 \text{ m}^3/\text{d}$ in 2040. Sensitivity analyses
19 of the parameters indicate that the unit price of electricity influences the utilization level of desalinated
20 seawater, and a complementary relationship is observed between reclaimed water and desalinated seawater.

21 **Keywords:** Water supply system; Desalinated plant capacity; Water resources allocation; Interval
22 programming; Stochastic programming; Uncertainties

23 1 Introduction

24 Increased water demand resulting from rapid socioeconomic development, intensive urbanization and the
25 uneven spatiotemporal distribution of natural water resources raised by climate change contributes to water
26 scarcity and brings difficulties in water resource planning and management (Milly et al. 2008; Mekonnen and
27 Hoekstra 2016). Traditional water supply sources will gradually fail to fulfill the increased water demand
28 (Paton et al. 2014; Larsen et al. 2016), and nonconventional water supply sources such as diverted water (DW),
29 reclaimed water (RW) and desalinated seawater (DSW) are being developed and utilized to alleviate water
30 scarcity (Beh et al. 2015). Compared to surface water supply sources, nonconventional sources have better
31 performance in terms of the stability of water quality and water quantity and are less vulnerable to global
32 warming (Beuhler 2003). Especially in economically developed coastal cities with abundant maritime
33 resources, desalinated seawater, characterized by small occupation, high stability and high water quality, is a
34 popular water supply alternative (Scarborough et al. 2015; Turner et al. 2016). The points of concern in
35 desalination are high energy consumption, economic cost and other environmental concerns (Heihsel et al.
36 2019). With the technological progress in desalination technology and the attention given to water scarcity,
37 the energy consumption and cost of desalinated seawater have continually decreased (Bennett, 2011; Bhojwani
38 et al., 2019), and the total capacity of all operating desalination plants in the world reached 92.5 million m³/d
39 in 2018 (Qasim et al. 2019; Nassrullah et al. 2020).

40 Nonconventional supply sources could be a supplement to traditional water supplies but cannot totally replace
41 them because of their properties. For example, diverted water projects occupy large areas, reclaimed water is
42 commonly used for nonpotable purposes, and the energy consumption in producing desalinated seawater is
43 high (Aliewi et al. 2017). Hence, multiple water resources constitute a moderate water supply system and are
44 recommended to be prioritized and developed in an integrated manner to maximize the advantages (Beuhler
45 2003). The determination of the proper capacity of a desalination plant is one of the key problems during the

development and utilization of desalinated seawater and should be considered in an integrated water supply system ([Hadjikakou et al. 2019](#); [Marlow et al. 2013](#); [Marques et al. 2015](#)).

Numerous approaches for desalinated seawater supply planning can be found in the literature. Research aimed at the determination of desalination plant capacity in water source planning has been conducted in coastal areas with strong dependency on desalinated seawater ([Mahmoud et al. 2002](#)). In terms of qualitative analysis, scholars have determined the priorities of different water supply sources in a multisource water supply system using, for example, the analytic hierarchy process ([Moglia et al. 2012](#)). In terms of quantitative methods, other research has aimed to determine the plant capacity and position of desalination plants using mathematical optimization methods considering cost and energy consumption ([Atilhan et al., 2011](#); [Liu et al., 2011](#); [Herrera-León et al., 2018](#); [Herrera-León et al., 2019](#); [Shahabi et al., 2017](#)). The appearance of intelligence algorithms has brought considerable research attention to the problem of water source planning and water allocation schemes in urban multisource water supply systems ([Bhushan and Ng, 2016](#); [Matrosov et al., 2015](#)). However, the uncertainties of input data are seldom considered in the literature mentioned above ([Paton et al., 2014](#); [Triantafyllidis et al., 2018](#)).

Uncertainties in water supply planning arise from multiple aspects, among which the uncertainties in hydrology and water demand present a challenge in obtaining optimal strategies ([Milly et al. 2008](#); [Li and Guo 2015](#); [Hui et al. 2018](#)). Given future uncertain events, if the plant capacity is insufficient, large economic losses would cause water shortages when extreme droughts occur, while the cost of desalinated seawater would increase if there is overcapacity in desalination. Uncertain optimization methods, such as interval programming ([Fu et al. 2017](#)), fuzzy programming ([Zhang et al. 2015](#)) and stochastic programming ([Erfani et al. 2018](#)), are often used to address these uncertainties. Meanwhile, these methods are also used in water allocation of multiple water resources ([Wang et al. 2017](#); [Li et al. 2018](#); [Dadmand et al. 2020](#)) and agricultural water and land allocation ([Cai and Rosegrant 2004](#); [Cai et al. 2016](#); [Chen et al. 2017](#)). [Fraga et al. \(2017\)](#)

proposed an integrated framework for short- and long-term water source planning based on dynamic programming and quadratic programming. The framework and results exhibited the features of the water supply infrastructure under increasing water demand and varying hydrologic conditions. To the best of our knowledge, there is no optimization model for desalinated seawater supply planning in an integrated multisource water supply system considering these uncertainties. The aim of this study is to address this gap and to develop a support tool for decision making regarding the development and utilization of desalinated seawater.

An interval-parameter two-stage stochastic programming model of optimal desalination plant capacity and a water allocation scheme are developed in this study to support urban water supply source planning. In this model, the uncertainties in water demand, benefits and economic losses caused by water shortages described as intervals and the uncertainty in stream flow described as a probability distribution are handled by introducing an interval in the two-stage stochastic programming model. The objective is to maximize the net benefit of the water supply system considering the energy consumption, economic cost and environmental impact of different water supply sources. The nonlinear cost function of desalinated seawater is linearized within the range of desalination plant capacity to solve the established model through linear programming. Finally, this model is applied to a case study of desalination planning in Weihai city, China.

2 Methods

The optimal model for the planning of urban nonconventional water source supply in this study is developed based on interval-parameter two-stage stochastic programming (ITSP) and the cost function of desalinated seawater (see Fig. 1). The development process of the model includes five main steps, as follows:

Fig. 1 Framework of medium-term urban desalinated seawater supply planning

Step 1: Analyze the intervals or the distributions of parameters and variables. The yearly water demands of multiple users in the study area were forecast based on predictions of the population, economic situation, and water use levels of users. These parameters are presented as discrete intervals with lower and upper bounds. The water availability of different supply sources was analyzed for each scenario.

Step 2: Fit the production cost function of desalinated seawater. According to the theory of economies of scale and the data associated with desalinated technology and costs in the study area, the production cost function of desalinated seawater was fitted based on the function proposed by Druetta et al. (2014).

Step 3: Develop the ITSP model. The ITSP model was developed based on the fitted production cost function of desalinated seawater. The objective function is the maximum system net benefit, and a constraint on the ratio of desalinated seawater to fresh water supplies is considered.

Step 4: Solve the upper-bound submodel. The ITSP model was transformed from a stochastic model into two deterministic models with upper and lower objective functions and solutions. The first-stage decision regarding the plant capacity in the planning period was determined by solving the upper-bound submodel.

Step 5: Solve the lower-bound submodel. The second-stage decision regarding the water allocation schemes of different kinds of supply sources was derived by solving the lower-bound submodel.

2.1 Interval-parameter two-stage stochastic programming

Fig. 2 shows the framework of the ITSP model, which is developed based on TSP and IPP to address dual uncertainties. Uncertainties are presented as discrete intervals in IPP and as probability distributions in TSP.

Fig. 2 Schematic of the ITSP model

TSP was proposed to address future uncertainties (Danzig 1955), the fundamental idea behind which is the concept of recourse (Maqsood et al. 2005). In TSP, an initial decision is made before future uncertain events occur, and recourse is taken when these uncertainties are later resolved. The initial decision is called the first-stage decision, and the corrective action is called the second-stage decision. In contrast to deterministic models with perfect knowledge of the future and parameters, scenario-based TSP supports current decisions with a number of future strategies corresponding to each scenario (Cai and Rosegrant 2004). Generally, a common two-stage stochastic programming problem can be defined as follows:

$$\begin{aligned}
 \max f &= cx + E[Q(x, \omega)] \\
 \text{s.t.} \quad & \\
 Ax &\leq b \\
 x &\geq 0
 \end{aligned} \tag{1}$$

where f is the objective function; x is the first-stage decision variable before stochastic variable ω is observed; and $Q(x, \omega)$ is the optimal solution of the second-stage problem, as follows:

$$\begin{aligned}
 \max q &(y, \omega) \\
 \text{s.t.} \quad & \\
 W(\omega)y + T(\omega)x &\leq H(\omega) \\
 y &\geq 0
 \end{aligned} \tag{2}$$

where y is the second-stage decision variable corresponding to a certain stochastic variable; $q(y, \omega)$ is the objective function; $\{W(\omega), h(\omega), T(\omega) | \omega \in \Omega\}$ denotes functions of ω ; ω corresponding to a probable level p_l is assumed to be ω_l ; and Eq. (1) could be expressed as follows:

$$\begin{aligned} \max f &= cx + \sum_{l=1}^n p_l q(y_l, \omega_l) \\ \text{s.t.} \\ Ax &\leq b \\ W(\omega_l)y_l + T(\omega_l)x &\leq H(\omega_l), \forall l=1, 2, \dots, n \\ x &\geq 0, y_l \geq 0 \end{aligned} \quad (3)$$

Huang and Loucks (2000) introduced an interval-parameter TSP formulation to address both the inherent parameter uncertainty and the difficulty in approximating the uncertainty with appropriate probability distributions. In addition, Eq. (3) can be expressed as the following ITSP formulation using the interval notation:

$$\begin{aligned} \max f^\pm &= c^\pm x^\pm + \sum_{l=1}^n p_l q(y_l^\pm, \omega_l^\pm) \\ \text{s.t.} \\ A^\pm x^\pm &\leq b^\pm \\ W(\omega_l^\pm)y_l^\pm + T(\omega_l^\pm)x^\pm &\leq H(\omega_l^\pm), \forall l=1, 2, \dots, n \\ x_l^\pm &\geq 0, y_l^\pm \geq 0 \end{aligned} \quad (4)$$

where $f^\pm$, $x^\pm$, $y^\pm$, and $\omega^\pm$ are interval variables with upper and lower bounds, and $f^\pm = [f^-, f^+]$.

A decision variable z is introduced to transform the nonlinear model (4) into a linear model. Let $x^\pm$ have a deterministic value of $x^- + \Delta x z$, where $\Delta x = x^+ - x^-$ and $0 \leq z \leq 1$. Model (4) can be transformed into two deterministic linear models. The upper-bound submodel is as follows:

$$\begin{aligned} \max f^+ &= c^+ (x^- + z\Delta x) + \sum_{l=1}^n p_l q(y_l^+, \omega_l^+) \\ \text{s.t.} \\ A^+ (x^- + z\Delta x) &\leq b^+ \\ W(\omega_l^+)y_l^+ + T(\omega_l^+)x^+ &\leq H(\omega_l^+), \forall l=1, 2, \dots, n \\ x^- &\geq 0, y_l^+ \geq 0 \end{aligned} \quad (5)$$

where z and y_l^+ are decision variables; the optimal solutions of model (5) are z_{opt} , $y_{l,opt}^+$, f_{opt}^+ , and $x_{opt}^\pm = x^- + z_{opt}\Delta x$.

The lower-bound submodel can be expressed as follows:

$$\begin{aligned}
& \max f^- = c^- (x^- + z_{opt} \Delta x) + \sum_{l=1}^n p_l q(y_l^-, \omega_l^-) \\
& s.t. \\
& A^- (x^- + z_{opt} \Delta x) \leq b^- \\
& W(\omega_l^-) y_l^- + T(\omega_l^-) (x^- + z_{opt} \Delta x) \leq H(\omega_l^-), \forall l = 1, 2, \dots, n \\
& y_l^- \leq y_{l,opt}^- \leq y_{l,opt}^+
\end{aligned} \tag{6}$$

where y^- is the decision variable; the optimal solutions of model (6) are $y_{l,opt}^-$ and f_{opt}^- . The optimum solutions of the interval-parameter two-stage stochastic programming model are $x_{opt}^\pm = x^- + \Delta x z_{opt}$, $f_{opt}^\pm = [f_{opt}^-, f_{opt}^+]$, and $y_{l,opt}^\pm = [y_{l,opt}^-, y_{l,opt}^+]$.

2.2 Cost function of desalinated seawater

Generally, the production cost of desalinated seawater includes capital expenditure and operation and maintenance expenditure. The former is dependent mainly on plant capacity and desalination technology, and the latter is affected by energy consumption and the utilization ratio. The production cost of desalinated seawater is considered a variable cost that can be reduced by increasing production efficiency when plant capacity is expanded and increased due to the decreasing marginal benefit when plant capacity reaches a certain level. Therefore, the cost function of desalinated seawater is expressed as a function of plant capacity and production yield, as follows (Druetta et al. 2014):

$$CDW = AF \cdot g(Cap) \cdot Cap + h(Cap, PY) \cdot PY \tag{7}$$

$$AF = \frac{IR(1+IR)^L}{(1+IR)^L - 1} \tag{8}$$

where CDW is the production cost of desalinated seawater; AF is the amortization factor; $g(Cap)$ denotes the unit capital cost of the desalination plant as a function of plant capacity (Cap); PY represents the production yield; $h(Cap, PY)$ denotes the unit operation and maintenance cost as a function of Cap and PY ; IR and L denote the annual interest rate and plant lifetime, respectively; and the values of IR and L are 0.049 and 25 in this paper.

The unit capital cost function $g(Cap)$ is expressed as follows (Lapiente 2012; Yu et al. 2017):

$$g(Cap) = \alpha \cdot \varphi \cdot \beta^{(Cap - Cap0)} + \zeta \quad (9)$$

where α and β are fixed coefficients equal to 0.37 and 0.95; φ denotes the unit capital cost when the plant capacity is equal to $Cap0$, and the values of φ and $Cap0$ are 10496 ¥ and 3 [10^4 m³/d]; ζ is the minimum unit capital cost, which is equal to 6325 ¥.

The unit operational cost function $h(Cap, PY)$ is as follows:

$$h(Cap, PY) = g(Cap) \cdot \delta^{PY} \quad (10)$$

where δ is an empirical coefficient equal to 0.975.

3 Case Study

3.1 Overall description of the study area

The optimal model was applied in the urban area of Weihai, the central city of Shandong Peninsula in eastern China. An important marine industry base and a tourist city, Weihai is located in the east of the Shandong Peninsula and is surrounded by the Yellow Sea on three sides (see Fig. 3). The urban area of Weihai is composed of two districts, Huancui and Wendeng.

Fig. 3 Location and division of Weihai

Affected by the north temperate continental monsoon climate, the city features four distinct seasons and monsoon climate characteristics. The annual average precipitation in Weihai is 770.6 mm, and the precipitation during the flood season from June to September accounts for 71.3% of the annual precipitation. Surface water resources occupy 37.7% of the annual average precipitation. This scenario reveals an uneven spatiotemporal distribution, and rivers in the city feature large gradients, which results in difficulty in utilizing surface water resources. The water resources per capita in the urban area are less than 233 m³, much less than the national mean. The vulnerabilities of the current urban water supply system make it necessary to develop nontraditional water supply sources to ensure water use security. The current water supply sources include surface water (SW), groundwater (GW), diverted water (DW) and a small amount of reclaimed water (RW). The water demands include household, urban productive (industrial, construction industry and domestic), ecological, environmental and agricultural water uses. Weihai represents a typical multiple water source and user system, and the logical relationship between water users and sources is presented in Table 1.

Table 1 The logical relationship between water users and sources

Surface water	Groundwater	Diverted water	Reclaimed water	Desalinated seawater
---------------	-------------	----------------	-----------------	----------------------

Household	1	1	1	0	1
Urban productive	1	1	1	1	1
Agricultural	1	1	0	0	0
Environmental	1	0	0	1	0
Ecological	1	0	0	0	0

Fig. 4 shows a generalized diagram of the urban water resource system of the study area, where the Mishan reservoir plays a dominant role because the annual quantity of water supplied by the Mishan reservoir in 2015 accounts for 70.7% of the urban water use, excluding agricultural water. The utilization of groundwater is limited for protection purposes. Water diverted from the Yangtze River and the Yellow River is delivered into the Mishan reservoir when droughts occur and surface water cannot fulfill the demands. According to the technological demonstration report of desalinated seawater (DSW) planning written by the administrative department of municipal construction of Weihai, a desalination plant is planned to be constructed in Huanchui to address its increased water use demand and land use situation, and reverse osmosis desalination technology is recommended.

Fig. 4 Generalized schematic of the water resource system in the study area

3.2 Model development

According to the ITSP, the planning of desalinated seawater utilization can be described as a two-stage problem: the first-stage problem is to determine an appropriate desalination plant capacity to satisfy water demand in the planning period; the second-stage problem is to generate water supply schemes under multiple uncertainties.

The objective of the optimal model in this paper is to maximize the system net benefits, which can be expressed as Eq. (11).

$$\max f^{\pm} = -CI(Cap^{\pm}) + \sum_s p_s (W_{i,j,s}^{\pm} B_{j,s}^{\pm} - W_{i,j,s}^{\pm} CO_{i,j,s} - WS_{j,s}^{\pm} L_{j,s}^{\pm}) \quad (11)$$

where $f^{\pm}$, $W^{\pm}$, $WS^{\pm}$, and $L^{\pm}$ represent intervals of parameters and variables; i, j , and s denote indexes of water sources ($i=1$ surface water, 2 groundwater, 3 reclaimed water, 4 diverted water, 5 desalinated seawater), users ($j=1$ household, 2 urban productive, 3 rural household, 4 agricultural) and scenarios ($s=1$ wet, 2 normal, 3 dry); CI is the capital cost of a seawater desalination plant, which is a function of plant capacity, Cap ; p is the probability of each scenario; W is the water amount supplied from a certain water source to a user; B denotes the benefit of water use; CO is the operation and maintenance costs of water supplies; L is economic losses caused by water shortage, WS .

The constraint conditions of the model include (1) supply and demand balance, (2) water availability, (3) engineering constraints and (4) nonnegativity constraints and can be expressed as follows:

$$Cap < UCap \quad (12)$$

$$\sum_i W_{i,j,s}^{\pm} + WS_{j,s}^{\pm} \leq D_{j,s}^{\pm} \quad (13)$$

$$W_{i,j,s}^{\pm} < WE_i^{\pm} \quad (14)$$

$$W_{i,j,s}^{\pm} < WA_{i,s}^{\pm} \quad (15)$$

$$k \cdot W_{5,j,s}^{\pm} < \sum_{i=1,4} W_{i,j,s}^{\pm} \quad (16)$$

$$W_{i,j,s}^{\pm} \geq 0 \quad (17)$$

where $UCap$ is the upper bound of desalinated plant capacity; $D^{\pm}$, $WE^{\pm}$, and $WA^{\pm}$ are intervals of parameters and variables; D is water demand; WE represents the water supply capacity; WA represents the water availability of water supply sources; k represents the ratio of desalinated seawater to fresh water ($k=3.5$ in this paper).

A decision variable of z is introduced to solve the model by transforming the original stochastic model into two deterministic submodels representing the upper and lower bounds. Let $Cap^{\pm}$ have a deterministic value of $Cap^{-} + \Delta Cap \cdot z$, where $\Delta Cap = Cap^{+} - Cap^{-}$ and $0 \leq z \leq 1$. The upper-bound submodel is as follows:

$$\max f^{+} = -CI \left(Cap^{-} + \Delta Cap \cdot z \right) + \sum_s p_s \left(W_{i,j,s}^{+} B_{j,s}^{+} - W_{i,j,s}^{+} CO_{i,j,s} - WS_{j,s}^{-} L_{j,s}^{-} \right) \quad (18)$$

s.t.

$$\sum_i W_{i,j,s}^{+} \leq D_{j,s}^{+}$$

$$W_{i,j,s}^{+} < WE_i^{+}$$

$$W_{i,j,s}^{+} < WA_{i,s}^{+}$$

$$k \cdot W_{5,j,s}^{+} < \sum_{i=1,4} W_{i,j,s}^{+}$$

$$W_{i,j,s}^{+} \geq 0$$

where z and $W_{i,j,s}^{+}$ are decision variables of the lower-bound submodel. The optimal solutions are expressed as z_{opt} and $W_{i,j,s,opt}^{+}$, and the lower-bound submodel is expressed as:

$$\max f^{-} = -CI \left(Cap^{-} + \Delta Cap \cdot z_{opt} \right) + \sum_s p_s \left(W_{i,j,s}^{-} B_{j,s}^{-} - W_{i,j,s}^{-} CO_{i,j,s} - WS_{j,s}^{+} L_{j,s}^{+} \right) \quad (20)$$

s.t.

$$\sum_i W_{i,j,s}^{-} \leq D_{j,s}^{-}$$

$$W_{i,j,s}^{-} < WE_i^{-}$$

$$W_{i,j,s}^{-} < WA_{i,s}^{-}$$

$$k \cdot W_{5,j,s}^{-} < \sum_{i=1,4} W_{i,j,s}^{-}$$

$$W_{i,j,s}^{-} \geq 0$$

The ITSP model can be solved through the above two submodels via linear programming, and the final optimal

solutions are:

$$Cap_{opt}^{\pm} = Cap^{-} + \Delta Cap \cdot z_{opt}, W_{opt}^{\pm} = [W_{opt}^{-}, W_{opt}^{+}] \quad (22)$$

3.3 Data

The base year and the planning years in this study are 2018 and 2030 and 2040, respectively. The main data for ITSP model establishment include the water demand forecast for five water users, the water availability and costs of five water supply sources and the benefits and economic losses of water shortage for different water users. Three scenarios were defined based on annual inflows: wet, normal and dry.

3.3.1 Water demand forecast

The upper-bound water demand in the planning years was set as the forecast from the water security planning of the Water Supplies Bureau and the Hydrographic Office of Weihai. The lower-bound water demand forecast was performed at the district scale for different water users. The household water demand was determined by multiplying the projected population and average household water demand per capita. The water demand for production was derived by multiplying the projected added value and average unit water consumption of different sectors. These parameters of the two districts in the planning year were derived by fitting the trends based on the data during 2001-2018. The agricultural water demands, consisting of irrigation and livestock, were determined based on the forecasts of cultivated area, average irrigation water demand per acre in all scenarios, quantity of livestock and average water demand for livestock. These parameters were projected based on the present values of 2018 with an assumed increase rate over the planning horizon. The water demand intervals are shown in Table 2.

Table 2 Intervals of water demand in the study area

Year	District	Scenario	Agricultural (10 ⁶ m ³)	Rural (10 ⁶ m ³)	Household (10 ⁶ m ³)	Urban productive (10 ⁶ m ³)	Environmental (10 ⁶ m ³)
2030	Huancui	Wet	[21.17, 23.46]	[2.1, 2.73]	[39.7, 43.73]	[55.62, 58.32]	[2.17, 2.41]

2040	Wendeng	Normal	[23.93, 27.24]	[5.27, 6.86]	[21.25, 29.09]	[46.27, 47.34]	[0.53, 0.58]
		Dry	[27.06, 31.64]				
		Wet	[63.09, 71.82]				
	Huancui	Normal	[72.98, 83.21]	[2.49, 3.02]	[46.01, 49.71]	[78.37, 80.15]	[2.79, 3.1]
		Dry	[84.48, 96.48]				
		Wet	[22.34, 24.01]				
	Wendeng	Normal	[25.26, 27.74]	[5.87, 7.11]	[27.33, 28.13]	[70.44, 73.23]	[1.48, 1.64]
		Dry	[28.58, 32.07]				
		Wet	[72.63, 79.25]				

3.3.2 Water availability

According to the analysis of the historical precipitation and stream flow data in the study area, the probabilities of the wet, normal and dry scenarios are assumed to be 0.2, 0.6 and 0.2, respectively. The available water supply data of the surface reservoirs under different scenarios are shown in Table 3. Other water sources are treated as stable water supplies in this study. The availability of those water sources was determined according to the water resource planning book established by the Water Supplies Bureau of Weihai and the Hydrographic Office of Weihai. The detailed data are presented in Table 4.

Table 3 Available water supply of reservoirs under all scenarios

Reservoir name	Available water supply of surface reservoirs (10 ⁶ m ³)		
	Wet scenario	Normal scenario	Dry scenario
	(Probability=0.2)	(Probability=0.6)	(Probability=0.2)
Mishan	[193.85, 265.34]	[55.9, 172.12]	[0, 53.66]
Wulin	[7.5, 10.51]	[1.9, 6.22]	[0.21, 2.07]
Guogezhuang	[7.09, 9.97]	[1.75, 5.6]	[0.2, 1.86]
Suoqianpo	[16.18, 23.2]	[5.92, 17.46]	[0.63, 6.07]
Gushan	[36, 54.53]	[8.22, 30.04]	[0.94, 8.76]
Poyu	[60.55, 89.43]	[24.22, 78]	[0.93, 14.63]
Kunlongxing	[45.54, 64.7]	[16.37, 50.1]	[1.5, 15.38]
Nanquan	[9.38, 12.49]	[3.51, 8.84]	[0.25, 3.23]

262 **Table 4** Availability of stable water supply sources in planning years

Planning year	District	Groundwater (10 ⁶ m ³)	Diverted water (10 ⁶ m ³)	Reclaimed water (10 ³ m ³ /d)
2030	Huancui	30.00	102	98
	Wendeng	62.00		42
2040	Huancui	30.00		132
	Wendeng	81.96		57

263 **3.3.3 Economic loss of water shortage**

264 Table 5 shows the unit economic losses for different users when water demands are not satisfied. The economic
 265 losses were determined based on economic data and water demand forecasts. The unit loss is larger than the
 266 unit benefit; if the water demand is not fulfilled, higher-priced alternatives would be chosen to satisfy the
 267 demand, or a reduction in benefit would be caused by a water shortage. Due to the difficulty in obtaining these
 268 parameters, the unit economic losses were calculated as the unit benefits multiplied by a coefficient of 1.2.
 269 The economic parameters of environmental and ecological users were set as the average level of agriculture.

270 **Table 5** Unit economic losses when water demands are not delivered

Planning year	District	Scenario	Agricultural (¥/m ³)	Household (¥/m ³)	Urban productive (¥/m ³)
2030	Huancui	Wet	[194, 217]	[3383, 3496]	[3213, 3308]
		Normal	[169, 187]		
		Dry	[146, 161]		
	Wendeng	Wet	[111, 121]	[3262, 3348]	[3166, 3244]
		Normal	[96, 104]		
		Dry	[83, 90]		
2040	Huancui	Wet	[210, 233]	[3709, 3807]	[3526, 3606]
		Normal	[183, 202]		
		Dry	[158, 174]		
	Wendeng	Wet	[132, 144]	[3624, 3672]	[3509, 3547]
		Normal	[115, 126]		
		Dry	[100, 109]		

271 **3.3.4 Cost of water supply**

272 The full costs of the water supply from different sources were determined as the sum of the resource cost,
 273 supply cost and environmental cost. The full costs of surface water, ground water, reclaimed water and diverted
 274 water are 3.2 ¥/m³, 4.5 ¥/m³, 3.6 ¥/m³ and 7.6¥/m³ in this study, and the detailed calculation can be
 275 found in (Zhang et al. 2020).

276 The resource cost and environmental cost of desalinated seawater are 0.12 ¥/m³ and 0.20¥/m³, respectively.
 277 The unit supply cost of desalinated seawater was determined according to the cost function mentioned above.
 278 Fig. 5 shows the unit cost of desalinated seawater under different plant capacities. Then, the cost function was
 279 transformed into two linear functions to solve the ITSP model. The interval of plant capacity was first
 280 determined: the lower bound was set to 30 10³ m³/d based on Cap_0 , and the upper bound was set to 120 10³
 281 m³/d by multiplying the plant capacity derived according to the forecasted water shortage by a coefficient of
 282 1.2. The unit operation and maintenance costs are shown in Table 6, where the labor and maintenance costs
 283 are assumed to be a linear function of the plant capacity and are included in the capital cost. The new capital
 284 cost function $CI(Cap)$, including $g(Cap)$ and a proportion of the operational costs, was linearized within the
 285 interval of plant capacity [30,120] (see Fig. 6).

Fig. 5 The unit cost function of desalinated seawater

Fig. 6 The linear capital cost function within the intervals of the plant capacity

286 **Table 6** The unit operation, resource and environmental costs of desalinated seawater

Item	Price (¥/m ³)	Remark
(1) Chemical consumption	0.58	

(2)	Membrane consumption	0.69	
(3)	Energy consumption	2.4	The price of electricity is 0.6 ¥/kWh.
(4)	Labor cost	0	(4)=0.028*Plant Capacity+1.1, [10^6 ¥], included in the capital cost.
(5)	Maintenance costs	0	1% of the capital cost, included in the capital cost.
(6)	Miscellaneous expenses	0.17	5% of the sum of the above, partially included in the capital cost.
(7)	Resource cost	0.12	
(8)	Environmental cost	0.20	Including the impacts of brine discharge and sewage disposal.
	Total	4.18	

4 Results

4.1 Capacity of desalinated plant and water strategies

This study aimed to optimize the desalinated plant capacity and water allocation strategy for multiple water sources considering the full costs of water sources. The optimal capacities of desalination plants in the planning years were derived by solving the two deterministic linear submodels, and the optimal capacity was $46 \times 10^3 \text{ m}^3/\text{d}$ in 2030 and $55 \times 10^3 \text{ m}^3/\text{d}$ in 2040. Clearly, the results revealed a larger capacity to fulfill the increasing water demand. A slight difference existed between the two capacities since the desalination plant was planned to be constructed in the Huancui district, and only the users in Huancui could use desalinated seawater.

The optimal water supplies from five kinds of water resources in three scenarios of two planning years are presented in Fig. 7. The priority of water supply sources is shown in Fig. 7, where the surface water supply has the highest priority, followed by groundwater, which emphasizes the advantages of traditional water resources for high water quality and quantity. As shown in Fig. 7, the surface water supply decreases significantly with decreasing flow level, and the surface water supply differs in the three scenarios due to the high uncertainty of the stream flow. The ground water supply was relatively stable in normal and dry scenarios since the ground water in the study area was limited to exact conditions for protective purposes.

Fig. 7 Intervals of optimal water supply schemes under different scenarios: (a) and (b) represent the results of 2030 and (c) and (d) represent the results of 2040

Reclaimed water is advantageous because of its low cost, and it played an important role in the water supply system of Wendeng due to its relatively low cost and the insufficiency of traditional water supplies. In this study, reclaimed water was assumed to undergo simple treatment and was allocated to users with a lower quality requirement, such as industrial and environmental sectors. The diverted water supplies accounted for the majority of the total water supply under the dry scenario, especially when the stream flow reached the

lower bound. For the target reservoir (Mishan), the diverted water could be treated as a controlled inflow to mitigate the variability of natural inflow. The proportion of water supplied by diverted water in 2040 declined compared to that in 2030 since the cost of diverted water was higher than that of reclaimed water. The intervals of desalinated seawater were $[16.36, 0] \times 10^6 \text{ m}^3$ and $[16.36, 16.27] \times 10^6 \text{ m}^3$ in 2030 under the normal and dry scenarios, respectively, where the former values in square brackets correspond to the water allocation when the objective value reached the lower bound. The proportion of water supplied by desalinated seawater increased in Huancui with the decrease in natural water availability, and the desalinated plant operated at almost full load under the dry scenario. Furthermore, the use of desalinated seawater is also limited by the ratio of desalinated seawater and fresh water to protect water supply pipes from erosion. Hence, the integrated optimization of the water strategy in a multisource water supply system is important.

4.2 Water allocation and risk analysis

The optimal water allocation schemes in 2030 and the water shortage situation under the three inflow levels are shown in Table 7 and Fig. 8. The amount of desalinated seawater supplied to household users in Huancui was more than that supplied to urban productive users under the normal and dry scenarios due to the higher priority of household users. The desalinated supply was constrained by the amount of fresh water, which resulted in more desalinated seawater supplied to household users under the dry scenario when solving the upper bound submodel than when solving the lower bound submodel. The water supply of urban productive users was also guaranteed in most scenarios in the two districts, except that a water shortage of $[0, 1.21] \times 10^6 \text{ m}^3$ was observed under the dry scenario in Wendeng in 2040. Agricultural users suffered heavy water scarcity under dry scenarios, and groundwater played an important role in irrigation water supply. In the model, the groundwater availability was determined according to the exploitation and replenishment balance, while the risk of groundwater overexploitation for irrigation existed in fact. To address this situation, appropriate future development of water saving irrigation technology is important, and the construction of desalination plants in

Wendeng is worth consideration to transform the structure of the water supply and fill the gap between the water demand and supply of household users and urban productive users. Meanwhile, since some urban water demand could be satisfied by desalinated seawater, limited natural water could be allocated to agricultural users to ensure regional water and food security.

341
342

(a)

343
344

(b)

Fig. 8 Water shortages in (a) 2030 and (b) 2040 under the three scenarios

4.3 System benefits and costs of water supply

The costs of water supplies, the benefits and losses of water shortages and the net system benefits are presented

in Fig. 9. Generally, the benefits and costs both increased from 2030 to 2040, and the system mean net benefit increased from $[622.21, 649.65] \times 10^9 \text{ ¥}$ in 2030 to $[782.78, 824.12] \times 10^9 \text{ ¥}$ in 2040. The economic losses under the dry scenario also increased from $[1.49, 6.32] \times 10^9 \text{ ¥}$ in 2030 to $[2.52, 18.8] \times 10^9 \text{ ¥}$ in 2040, which revealed that the water supply system showed less robustness in 2040. With the decrease in surface water availability, the benefits and net benefits decreased, and the costs of water supply and the economic losses caused by water shortages increased. According to the water shortage situation, the economic losses were caused mainly by the agricultural water shortage under the normal scenario and the losses due to water shortages in households and urban productivity under the dry scenario.

Fig. 9 System benefits and costs of water supply in (a) 2030 and (b) 2040

359 **Table 7** Intervals of water allocation among sources to users in 2030 under three scenarios

Scenarios	District	User	Supplies from Huancui water resources (10 ⁶ m ³)				Supplies from Wendeng water resources (10 ⁶ m ³)			Diverted water (10 ⁶ m ³)
			Surface Water	Groundwater	Reclaimed water	desalinated seawater	Surface Water	Groundwater	Reclaimed water	
Wet	Huancui	Household	[16.31,16.75]	[0,0]		[0,0]	[30.25,29.81]			[0,0]
		Urban productive	[14.74,15.06]	[0,0]	[0,0]	[0,0]	[43.58,43.26]			[0,0]
		Agricultural	[23.46,21.17]	[0,0.88]						
		Ecological	[21.51,30.55]							
	Wendeng	Household	[4.82,4.71]				[31.57,31.69]	[0,0]		[0,0]
		Urban productive	[5.5,5.38]				[41.84,41.96]	[0,0]	[0,0]	[0,0]
		Agricultural					[45.5,52.89]	[26.32,14.46]		
		Ecological					[37.9,51.96]			
Normal	Huancui	Household	[11.55,18.04]	[3.67,0]		[10.04,0]	[8.14,28.52]			[13.16,0]
		Urban productive	[9.58,17.01]	[5.41,0]	[20.41,0]	[6.71,0]	[6.83,41.31]			[9.38,0]
		Agricultural	[16.15,23.93]	[8.09,0.98]						
		Ecological	[8.47,23.01]							
	Wendeng	Household	[3.93,3.94]				[14.46,32.46]	[6.52,0]		[11.49,0]
		Urban productive	[3.78,4.22]				[11.33,43.12]	[7.04,0]	[15.46,0]	[9.73,0]
		Agricultural					[33.12,46.13]	[48.43,29.72]		
		Ecological					[11.95,35.24]			
Dry	Huancui	Household	[1.08,8.21]	[3.67,3.73]		[9.71,10.21]	[0,6.71]			[32.1,17.71]
		Urban productive	[1.05,7.16]	[5.41,5.76]	[20.41,20.41]	[7.04,6.45]	[0,5.8]			[24.41,12.75]
		Agricultural	[0,14.5]	[8.09,8.3]						

	Ecological	[0.88,7.15]					
Wendeng	Household	[0.3,2.94]		[0.87,13.27]	[9.41,5.39]		[23.2,14.79]
	Urban productive	[0.27,3.11]		[0.68,12]	[7.57,6.29]	[15.46,15.46]	[22.29,10.48]
	Agricultural			[0.17,32.55]	[45.02,50.32]		
	Ecological			[0.68,11.42]			

361 5 Discussion

362 5.1 Sensitivity analysis

363 The cost of energy consumption accounts for over 55% of the operational cost of desalinated seawater in
364 this model under the condition that the unit price of electricity is 0.6 ¥/kWh. This price was determined
365 according to the average price of the electricity supplied to the industry and commercial sectors in Weihai.
366 To assess the influence of the unit electricity price on the results, a series of unit price values were set in
367 the model. The variation in mean desalinated seawater use and the average unit price of the water supply
368 are presented in Fig. 10. As the unit electricity price decreased, the mean desalinated seawater use
369 increased, and the unit price of desalinated seawater decreased linearly. The variation in the average unit
370 price of the water supply among all water sources barely changed with the variation in the unit electricity
371 price because desalinated seawater accounted for less than [0.9%, 4.1%] of the total water supply. For
372 desalinated seawater supply enterprises, a preferential policy of unit electricity price could decrease the
373 unit price of desalinated seawater to decrease operational costs.

374 The use rate of reclaimed water was assumed to be 0.35 in 2030 and 0.40 in 2040 according to the
375 reclaimed water planning in Weihai. This parameter represents the utilization level, equipped capacity
376 and technology of reclaimed water, and the values in the model are relatively ideal since the use rate of
377 reclaimed water in urban productive water was 0.11 in 2018. A series of use rates was set to explore the
378 influence on desalinated seawater planning. The results in 2030 under different values of use rate are
379 shown in Fig. 11. A decrease in the use rate led to an increase in desalinated plant capacity and the use of
380 diverted water and desalinated seawater. A complementary relationship between the reclaimed water
381 supply and the other two nonconventional water supplies, desalinated seawater and diverted water, is
382 observed in Fig. 11. Furthermore, a larger water shortage of household users occurred in Wendeng under
383 the dry scenario when the use rate of reclaimed water decreased further. Since the reclaimed water supply

decreased and more limited diverted water was allocated to users in Huancui, urban water use should be secured by natural water resources and multiple nonconventional water resources.

Fig. 10 The variation in desalinated seawater use and price of water supply

Fig. 11 Variation in nonconventional water supplies and desalinated plant capacity with changes in the use rate of reclaimed water

5.2 Limitations and further possible extensions

This study has some limitations. First, the ITSP model has advantages in addressing the uncertainties of stream flow and parameters while the nonlinearity of parameters is not considered. The economies of scale of desalinated seawater were not considered since within a certain range of desalinated plant capacity, the influence of economies of scale was negligible. Second, the costs of water supplies except desalinated seawater were considered constant in the model due to data availability and the linear requirement of the model. The nonlinearity of the water supply cost and other parameters, such as the benefit, economic loss caused by water shortage and the variable cost of all water supplies, are worth consideration in future research. Third, this study focused on the planning of desalinated seawater, and we found that the results were sensitive to the use rate of reclaimed water. The uncertainty in the use rate could be considered in further exploration.

The water supply system consists of natural water resources (uncontrolled) and nonconventional water resources (controlled), and the latter could be regarded as a supplement and regulation resource for the

399 former. The ITSP model developed in this study was implemented on a year scale, and the unevenness of
400 natural stream flow within a year was generalized. Further possible extension of the optimal model of
401 water supply planning includes a shorter time scale, consideration of the supplement of nonconventional
402 water supplies to natural water supplies and the operation of engineering and the influence of climate
403 change. The objective function of the model was the maximum system net benefit, and the energy
404 consumption and environmental impact were included in the full cost of the water supply. Factors that
405 could be further considered in future studies include water quality, greenhouse gas emissions, and social
406 acceptance. In addition, in light of the complementary relationship among nonconventional water supplies,
407 the model framework could be extended from desalination to multiple water supply source planning.

408 **6 Conclusion**

409 Coastal areas are superior in the utilization of seawater, and desalinated seawater has become an important
410 component in urban water supply systems when uneven and limited natural water resources are
411 insufficient to fulfill increasing water demand. An interval-parameter two-stage stochastic programming
412 model was established in this research by considering a linearization of the cost function of desalinated
413 seawater, which contributes to urban nonconventional water source planning and management. The
414 objective of the model was to maximize the system net benefits considering the full cost of water supplies.
415 A constraint on the rate of desalinated seawater supply and fresh water was set to 3.5 to maintain the
416 safety of the water supply pipes. The uncertainties in the water supply system, described as discrete
417 intervals and probability distributions, including water demand, water use benefit, economic loss caused
418 by water shortage and water availability of surface water resources, were addressed by introducing an
419 interval parameter into the two-stage stochastic programming model. The model developed in this study
420 requires no detailed technological data and can be extended to similar coastal regions suffering water
421 scarcity where capital cost and operational cost data of water supplies are available.

The developed model was applied to a realistic case in Weihai, China, where natural water and nonconventional water compose the multiple-source water supply system. Three scenarios with different levels of surface water availability were considered to optimize the desalinated plant capacity and water allocation scheme in the urban area of Weihai. The results suggested a greater need for desalination in 2040 than 2030 to satisfy the increasing water demand of urban users, and desalination must also be considered in Wendeng in 2040 due to the water shortage occurring for urban users. The water allocation schemes showed that a multiple-source water supply system was more robust than a system depending on natural water resources, which had high unevenness. The influence of the unit price of electricity on the operation cost of desalination is reflected in the utilization level of desalinated seawater, and a preferential policy of the unit electricity price contributes to the utilization level of desalinated seawater. Under the low availability of surface water, nonconventional water supplies become an important supplement to the natural water supply to guarantee water security. A complementary relationship was found among nonconventional water supplies, especially between reclaimed water and desalinated seawater, in that the desalinated plant capacity revealed high sensitivity of the use rate of reclaimed water. This result emphasizes the importance of integrated planning and management of nonconventional water supplies, which need further research in the future.

Declarations

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Availability of data and material Some or all data that support the findings of this study are available from the corresponding author upon reasonable request.

Code availability Some or all code that support the findings of this study are available from the corresponding author upon reasonable request.

Authors' contributions Zongzhi Wang prepared the manuscript with contributions from all co-authors. Ailing Ye and Zongzhi Wang developed the model. Kelin Liu and Liting Tan guided and participated in the modelling. Ailing Ye made the electric artworks and words processing.

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Figures

Figure 1

Framework of medium-term urban desalinated seawater supply planning

Figure 2

Schematic of the ITSP model

Figure 3

Location and division of Weihai. Note: The designations employed and the presentation of the material on this map do not imply the expression of any opinion whatsoever on the part of Research Square concerning the legal status of any country, territory, city or area or of its authorities, or concerning the delimitation of its frontiers or boundaries. This map has been provided by the authors.

Figure 4

Generalized schematic of the water resource system in the study area

Figure 5

The unit cost function of desalinated seawater

Figure 6

The linear capital cost function within the intervals of the plant capacity

Figure 7

Intervals of optimal water supply schemes under different scenarios: (a) and (b) represent the results of 2030 and (c) and (d) represent the results of 2040

Figure 8

Water shortages in (a) 2030 and (b) 2040 under the three scenarios

Figure 9

System benefits and costs of water supply in (a) 2030 and (b) 2040

Figure 10

The variation in desalinated seawater use and price of water supply

Figure 11

Variation in nonconventional water supplies and desalinated plant capacity with changes in the use rate of reclaimed water