Dear Referee #1,

We highly appreciate your review and useful comments on our manuscript again. We have made appropriate revisions according to your comments and provided our responses to your queries below.

Kind regards, all authors

Queries by anonymous referee #1 & answers by authors are as follows:

Specific Comments:

(1) It is very important that the Figure 1, in which the MOEAs and NSGA-II should appear, must be logically and carefully explained.

Authors' response: Thanks for your constructive comments. The multi-objective evolutionary algorithms (MOEAs) are used to optimize the parameterized policies. The MOEAs associated with the AI-based management methodology is present in Figure 1.

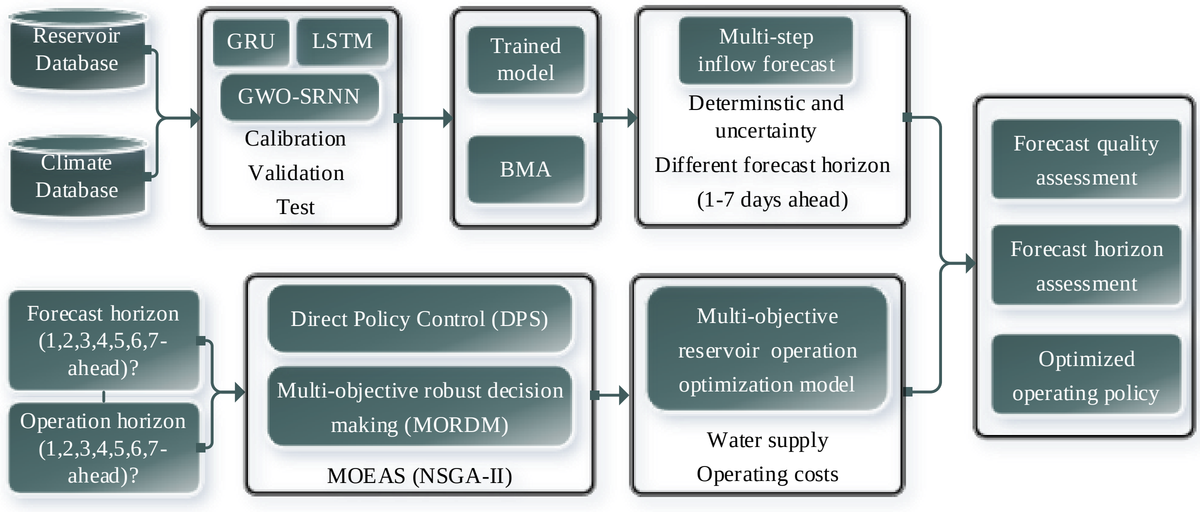

Figure 1: Framework of the AI-based management methodology.

We have added more explanations in the revised version to explain how MOEAs are used in the parameterized MORDM method and presented in Figure 3. Please see Page 11, Lines 243-246.

"*(4) Optimizing the parameterized policies using multi-objective evolutionary algorithms (MOEAs) based on the robust performance objectives. Repeat Steps (2), (3), and (4) until the times of population iteration are reached and then export the optimal Pareto solutions. In this study, the optimization is solved by applying NSGA-II to search the space of decision variables and identify the trajectories.*

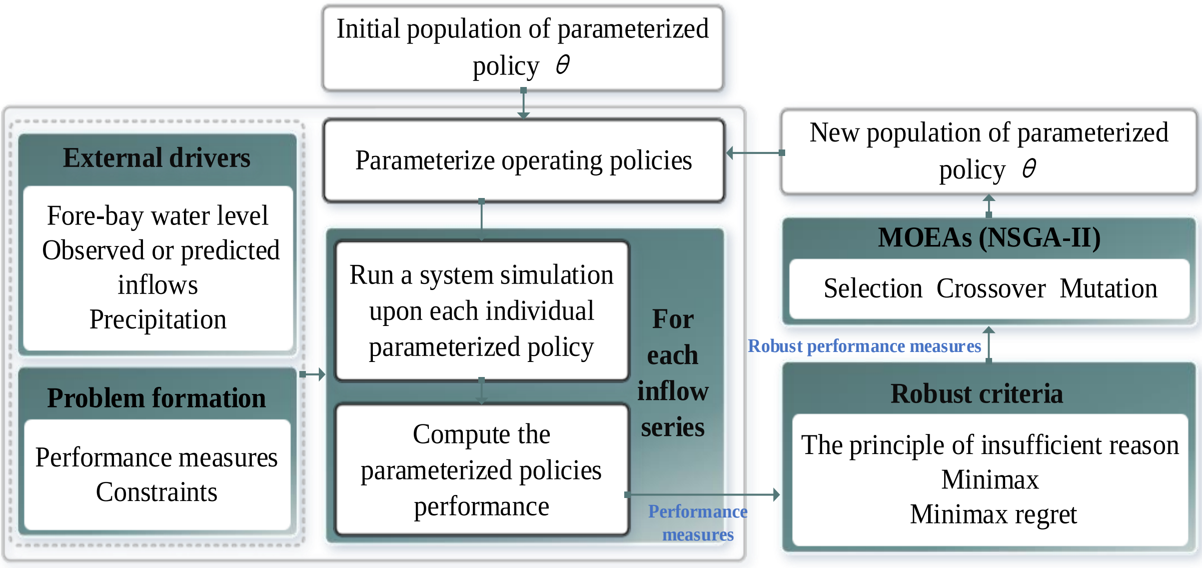

Figure 3: Schematization of the parameterized MORDM methods.

(2) It should be clearly explained on how the hydrological variables are related to the mathematical variables in LSTM, GRU and GWO-LSSVM. By the way, the model forecast (f) in (18) cannot be found in the model GRU, why?

Authors' response: Thanks for your constructive comments. The hydrological variables are used as the inputs (x) in LSTM, GRU, and GWO-LSSVM. The mapping function (i.e., model forecast) between the forecasted streamflow Q_t and hydrological variables x_t can be represented by $f(\cdot)$. In LSTM and GRU, $Q_t = f(x_t, h_{t-1})$ (h_{t-1} denotes the last hidden cell state and the initial state of h_t is h_0= 0), while in GWO-LSSVM, $Q_t = f(x_t)$. The f_t in Eq.1 of the previous manuscript represents the forget gate in LSTM. We have revised it as g_t to avoid confusion. To answer your question, we have modified it in the revised version.

Please see Page 4, Lines 111-113.

"In this study, the mapping function between the forecasted streamflow Q_t and hydrological variables x_t can be represented by $f(\cdot)$. In LSTM and GRU, $Q_t = f(x_t, h_{t-1})$ (h_{t-1} denotes the last hidden cell state and the initial state of h_t is h_0= 0), while in GWO-LSSVM, $Q_t = f(x_t)$."

Please see Page 4, Lines 121.

"Forget gate: $$g_t = \sigma(W_f x_t + U_f h_{t-1} + b_f), \quad (1)$$

Please see Pages 15-16, Lines 342-348.

"In this case, the streamflow can be forecasted using the following equations, given S3 as an example.

$$\begin{aligned} &\text{1d: } Q_{t+1}^{f} = f\left(Q_t, Q_{t-1}, ..., Q_{t-k}, E_t, E_{t-1}, ..., E_{t-k}, P_{t-1}, ..., P_{t-k}\right) \\ &\text{2d: } Q_{t+2}^{f} = f\left(Q_t, Q_{t-1}, ..., Q_{t-k}, E_t, E_{t-1}, ..., E_{t-k}, P_{t-1}, ..., P_{t-k}\right) \\ &... \\ &\text{7d:: } Q_{t+7}^{f} = f\left(Q_t, Q_{t-1}, ..., Q_{t-k}, E_t, E_{t-1}, ..., E_{t-k}, P_{t-1}, ..., P_{t-k}\right) \end{aligned} \tag{54}$$

where $f(\cdot)$ *is the mapping function between inputs and outputs, which can be modelled by LSTM, GRU, and GWO-LSSVM in our case. The hydrological variables normalized to the same scale of [0, 1] are used as the inputs (x) in the three ML methods. The normalization equation is given as follows:*

$$x' = \frac{x - x_{\min}}{x_{\max} - x_{\min}}, \tag{55}$$

where x *and* x' *are the original and normalized values, respectively.* $x_{\min}$ *and* $x_{\max}$ *are the minimum and maximum values of the original series, respectively."*

(3) Why you need generate a realization of observation (y_t), rather than using the historically observed (Line 177)? Also, it is not clear where this "y_t" has been used in the following models.

Authors' response: Thanks for your constructive comments. We are sorry for the confusion. The "observation (y_t)" should be "forecasts Q_t". The ensemble forecasts $Q_{T\times M}$ are employed to represent the stochastic forecasts in the following models. To answer your question, we have modified it in the revised version. Please see Page 8, Lines 175-182.

"Then we use the Monte Carlo simulation method to generate BMA ensemble forecasts. Assume M is the number of Monte Carlo simulations, and the procedure is described below (Zhou et.al., 2020a).

(a) Set the initial cumulative weight $w_0^* = 0$ *and calculate the cumulative weight* $w_k^* = w_{k-1}^* + w_k$ *for k=1,2,..., K. Create a random variable u between 0 and 1. If* $w_{k-1}^* \le u \le w_k^*$, *the* k^{th} *forecast model would be used as the target forecast.*

(b) Generate a realization of the forecasts Q_t *using the Gaussian distribution function* $g\left(Q_t \mid f_k^t, \sigma_k^2\right)$. *In such a way, there are a set of alternative forecasts to be chosen from as the final forecast.*

(c) Repeat Steps (a) & (b) for M times and obtain a set of streamflow series $Q_{T\times M} = \begin{bmatrix} Q_{1,1} & Q_{2,1} & \cdots & Q_{T,1} \\ Q_{1,2} & Q_{2,2} & \cdots & Q_{T,2} \\ \vdots & \vdots & \ddots & \vdots \\ Q_{1,M} & Q_{1,M} & \cdots & Q_{T,M} \end{bmatrix}$*. Furthermore, 90% confidence intervals between the 5% and 95% quantities are employed to represent the uncertainty of BMA ensemble forecasts."*

References

Zhou, Y., Chang, F.-J., Chen, H., et al. Exploring Copula-based Bayesian Model Averaging with multiple ANNs for PM2.5 ensemble forecasts. Journal of Cleaner Production, 263, 121528, https://doi.org/10.1016/j.jclepro.2020.121528, 2020a.

(4) Based on the procedure in Lines 175-179, why you need simulate a large number (M =1000) of forecasts since there are only three optional forecasts to be repeatedly chosen from?

Authors' response: Thanks for your comments. Previous studies have identified that real-time reservoir operations were influenced by multiple uncertainties (Xu et al., 2020), among which inflow forecast uncertainty (e.g., forecast model uncertainty) has been determined as the primary source. BMA (Hoeting et al., 1999) has been found to be an effective and commonly used method to evaluate uncertainty. BMA ensemble forecasts can be obtained using the Monte Carlo simulation method based on the individual model forecasts. The number of Monte Carlo simulations is set as 1000, as Zhou et al. (2020a) used in their study. At each forecast time, the k^{th} model forecast can be selected according to Step (a), and the forecasts Q_t is then obtained using the Gaussian distribution function $g\left(Q_t \mid f_k^t, \sigma_k^2\right)$ according to Step (b). In such a way, there are not only three optional forecasts to be chosen from but a set of forecasts (the Gaussian distribution of $g\left(Q_t \mid f_k^t, \sigma_k^2\right)$) to be chosen from. We are very sorry for the confusion. To answer your question, we have modified it in the revised version. Please see Page 8, Lines 179-180.

"(b) Generate a realization of the forecasts Q_t using the Gaussian distribution function $g\left(Q_t \mid f_k^t, \sigma_k^2\right)$*. In such a way, there are a set of alternative forecasts to be chosen from as the final forecast."*

References

Hoeting, J. A., Madigan, D., Raftery, A. E., et al. Bayesian Model Averaging: A Tutorial. Statistical Science, 14(4), 382-417, https://www.jstor.org/stable/2676803, 1999.

Xu, B., Zhong, P.-a., Lu, Q., et al. Multiobjective stochastic programming with recourses for real-time flood water conservation of a multireservoir system under uncertain forecasts. Journal of Hydrology, 590, 125513, https://doi.org/10.1016/j.jhydrol.2020.125513, 2020.

Zhou, Y., Chang, F.-J., Chen, H., et al. Exploring Copula-based Bayesian Model Averaging with multiple ANNs for PM2.5 ensemble forecasts. Journal of Cleaner Production, 263, 121528, https://doi.org/10.1016/j.jclepro.2020.121528, 2020a.

(5) From Line 214 to 225: this is where you should make very good efforts to logically clarify how the MORDM is coupled with the deterministic and stochastic forecasts, the DPS, the optimization problem of up to 7 days ahead with the MOEAs /NSGA-II, especially, how the performances /objectives are evaluated when optimizing the operating policy (p_θ)?

Authors' response: Thanks for your comments. We have added more details and a figure to clarify the method. Please see Pages 10-11, Lines 220-248.

"In our study, the parameterized MORDM approach will be coupled with a rolling horizon scheme over one year period to solve the multi-objective reservoir operation problem. Given the lead time of 7 days (forecast horizon is equal to operation horizon) as an example, it is operated following two steps: the optimization model is first operated daily over a 7-day horizon using the parameterized MORDM; after implementing current water allocation decisions, the status of the system inflow, and other information of reservoirs update as time evolves, and then the remainder is subsequently operated. The two steps are repeated until the process (one year period) is completed. In each operating horizon, the main steps of the parameterized MORDM are described below and present in Figure 3.

(1) Problem formulation, including the performance measures and constraints.

(2) Generate alternative parameterized policies subjecting to all the constraints, and the objectives are evaluated over stochastic inflows with the following procedures (Giuliani et al., 2016):

a) The operating policies are parameterized using RBFs;

b) Run a system simulation from t=1,2,…7d upon each individual parameterized policy p_θ for each inflow series and obtain the system trajectories;

c) Compute the parameterized policies performance in terms of the operating objectives as a function of system trajectories.

(3) Recompute the parameterized policies performance with robust criteria, for instance, the principle of insufficient reason, minimax, and minimax regret (Guo et al., 2020b). Among them, the principle of insufficient reason transforming the problem under uncertainty into a decision-making problem under risk has been used in the water resources problems (Giuliani and

Castelletti, 2016). The principle of insufficient reason suggests that in the absence of knowledge on the probabilities associated with the different states, the decision could be taken by assigning equal probability to all states (i.e., $P_j = 1/n$ *). The robust parameterized policies performance can be expressed as:*

$$\min \left(\frac{1}{n} \sum_{j=1}^{n} Obj(p_\theta, s_j) \right), \tag{34}$$

where $Obj(p_\theta, s_j)$ *is the performance function using parameterized policy* p_θ *upon* j^{th} *streamflow series,* s_j *denotes the scenario of the* j^{th} *streamflow series, and n is the number of stochastic streamflow series.*

(4) Optimizing the parameterized policies using multi-objective evolutionary algorithms (MOEAs) based on the robust performance objectives. Repeat Steps (2), (3), and (4) until the times of population iteration are reached and then export the optimal Pareto solutions. In this study, the optimization is solved by applying NSGA-II to search the space of decision variables and identify the trajectories.

It should be noted that the parameterized MORDM in this study aims to solve optimization problems under uncertainty, and thereby one streamflow series need to be repeated multiple times.

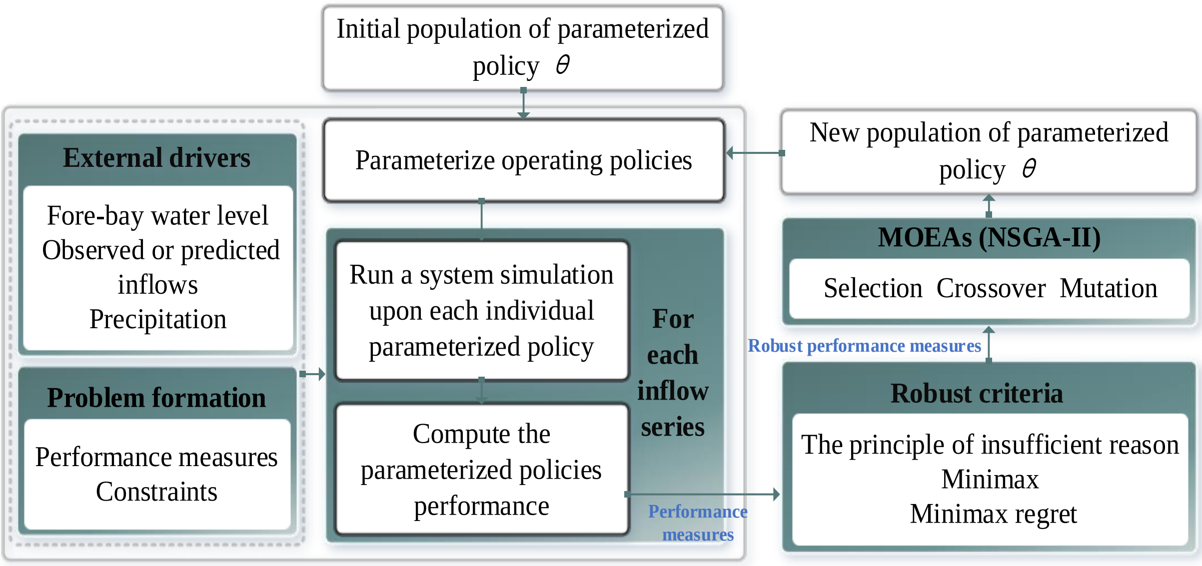

Figure 3: Schematization of the parameterized MORDM methods.

References

Guo, Y., Fang, G., Xu, Y.-P., et al. Responses of hydropower generation and sustainability to changes in reservoir policy, climate and land use under uncertainty: A case study of Xinanjiang Reservoir in

China. Journal of Cleaner Production, 124609, https://doi.org/10.1016/j.jclepro.2020.124609, 2020b.
Giuliani, M., Castelletti, A. Is robustness really robust? How different definitions of robustness impact decision-making under climate change. Climatic Change, 135(3-4), 409-424, https://doi.org/10.1007/s10584-015-1586-9, 2016.
Giuliani, M., Castelletti, A., Pianosi, F., et al. Curses, tradeoffs, and scalable management: Advancing evolutionary multi-objective direct policy search to improve water reservoir operations. Journal of Water Resources Planning and Management, 142(2), 04015050, https://doi.org/10.5334/jors.293, 2016.

(6) Please check on Line 281, why it is the release from a reservoir that is refined to make a pumping flow feasible?

Authors' response: As presented in Figure 5, the reservoirs supplying plants can be divided into two categories. Some reservoirs can directly release water into the plants or reservoirs, including Longtan, Ludong, Shatianao, Nanao, Chenao, Cengang, Tuanjie, and Changchunling reservoirs, while the other reservoirs can only release water into the plants or reservoirs using pumping stations. Assume that $Q_{t,j}^{p}$ denotes the j^{th} pumping flow at t^{th} time step in (m^3/s), $Q_{t,n}^{r}$ is the release of the n^{th} reservoir at t^{th} time step in (m^3/s), and N is the number of reservoirs pumped by the j^{th} pumping station, and the pumping flow ($Q_{t,j}^{p}$) can be summed by reservoir releases ($Q_{t,n}^{r}$) pumped by the corresponding pumping station, $Q_{t,j}^{p}=\sum_{n=1}^{N}Q_{t,n}^{r}$. We have added some explanations in the revised version. Please see Page 12, Lines 275-282.

"Releases from the reservoirs (Huangjinwan Reservoir and the remaining 24 local reservoirs) have to meet the water plants requirements. As observed in Figure 5, the reservoirs supplying plants can be divided into two categories. Some reservoirs can directly release water into the plants or reservoirs, including Longtan, Ludong, Shatianao, Nanao, Chenao, Cengang, Tuanjie, and Changchunling reservoirs. In contrast, the other reservoirs can only release water into the plants or reservoirs using pumping stations. In such a way, the pumping flow can be obtained by summing reservoir releases through the corresponding pumping station, using the following equation.

$$Q_{t,j}^{p}=\sum_{n=1}^{N_1}Q_{t,n}^{r}\ , \qquad (35)$$

where $Q_{t,j}^{p}$ *denotes the j^{th} pumping flow at t^{th} time step in (m^3/s),* $Q_{t,n}^{r}$ *denotes the release of the n^{th} reservoir at t^{th} time step in (m^3/s), and N_1 is the number of reservoirs pumped by the j^{th} pumping station.*

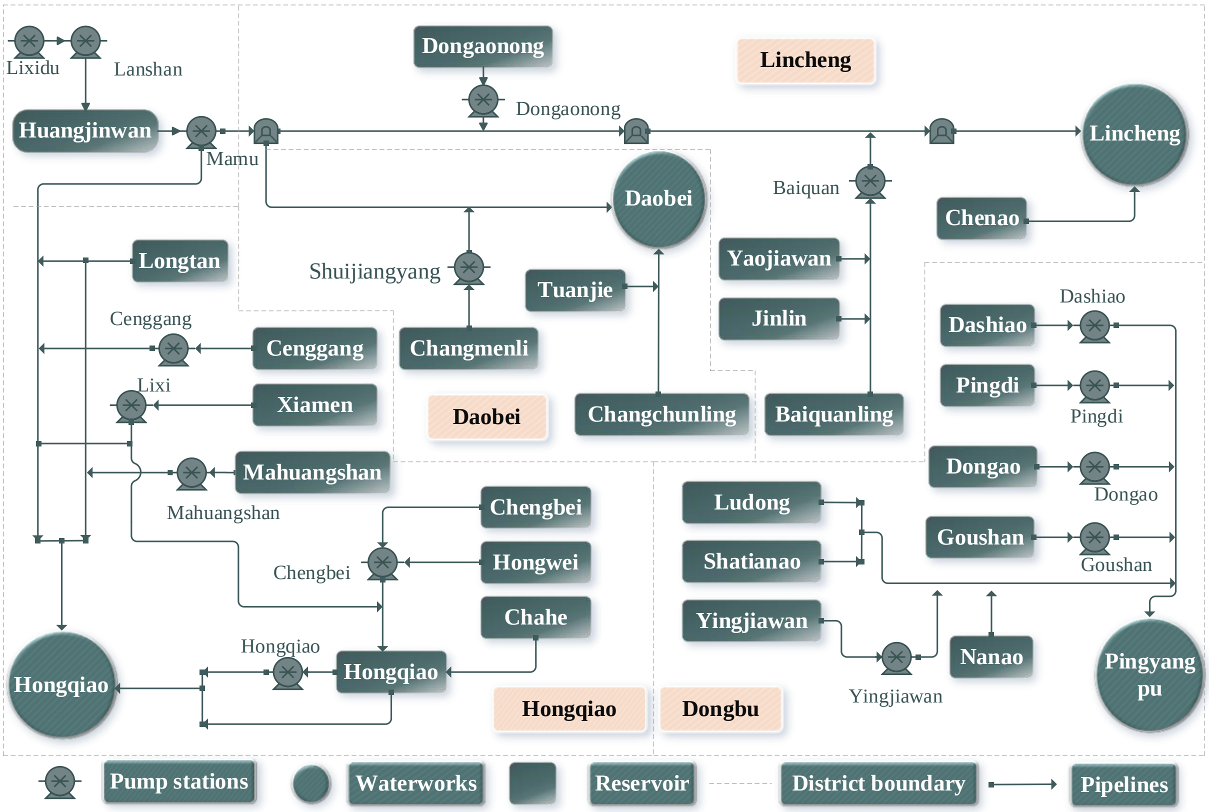

Figure 5: Schematic diagram of Zhoushan Islands."

(7) Please improve on the optimization problem formulation in a more professionally mathematical way. The relationship between variables is incomplete. The hydraulic relationship / connections, for instance, between reservoirs, pumps, channels and water demanders, are not logically presented.

Authors' response: Thanks a lot for your insightful suggestion. We have modified the problem formulation in the revised version. Please see Pages 12-13, Lines 264-295.

"*Figure 5 shows the simplified schematic diagram of the water supply system in Zhoushan Islands, including reservoirs, pumping stations, pipelines, and water plants. The pipeline arrow indicates the direction of the water flow. It covers the processes associated with water abstraction from resources, water distribution through the network involving the use of pumping stations and pipelines, and main activities relevant to water flow. In this study, water resources include local surface water and imported water. The surface water is the water stored in local reservoirs (a number of 24 reservoirs), while the imported water is the water transferred from Ningbo City (stored in Huangjinwang Reservoir). The imported water is transferred from Ningbo City to Zhoushan Islands through Lixidu and Lanshan pumping stations. End-users within the water supply system are generally divided into the household, industry, agriculture, and environmental use. This study mainly considers household and* *industry use, which water plants can supply. The agriculture and environmental use are satisfied through operating the reservoir storage above a specific value. That is to say, the main goal of the water allocation plan is to ensure sufficient water flows into the four plants in Zhoushan Islands. They are Daobei, Lincheng, Hongqiao, and Pingyangpu plants, respectively. Releases from the reservoirs (Huangjinwan Reservoir and the remaining 24 local reservoirs) must meet the requirements of water plants. As observed in Figure 5, the reservoirs supplying plants can be divided into two categories. Some reservoirs can directly release water into the plants or reservoirs, including Longtan, Ludong, Shatianao, Nanao, Chenao, Cengang, Tuanjie, and Changchunling reservoirs. In contrast, the other reservoirs can only release water into the plants or reservoirs using pumping stations. In such a way, the pumping flow can be obtained by summing reservoir releases through the corresponding pumping station, using the following equation.*

$$Q_{t,j}^{p} = \sum_{n=1}^{N_1} Q_{t,n}^{r}\,, \qquad (35)$$

where $Q_{t,j}^{p}$ *denotes the* j^{th} *pumping flow at* t^{th} *time step in* (m^3/s), $Q_{t,n}^{r}$ *denotes the release of the* n^{th} *reservoir at* t^{th} *time step in* (m^3/s), *and* N_1 *is the number of reservoirs pumped by the* j^{th} *pumping station.*

It can be noted in Figure 5 that there are no specific hydraulic connections between most of the reservoirs, while Chahe, Hongwei, Chengbei, and Xiamen reservoirs can release water into Hongqiao Reservoir (the largest reservoir in Zhoushan Islands). With a water plant as a center, the whole islands are divided into four districts, i.e., Daobei, Lincheng, Hongqiao, and Dongbu. The dashed line represents the district boundary. Each district includes a water plant, several pumping stations, and reservoirs to supply water for the water plant. The hydraulic connection between such a water plant and corresponding pumping stations and reservoirs can be expressed as:

$$W_{t}^{s} = \sum_{j=1}^{J} Q_{t,j}^{p}\Delta t + \sum_{n=1}^{N_2} Q_{t,n}^{r}\Delta t\,, \qquad (36)$$

where W_{t}^{s} *is the amount of water supply for a water plant at* t^{th} *time step* (m^3), *J is the number of pumping stations flowing into the water plant, and* N_2 *is the number of reservoirs directly releasing into the water plant.*

In Figure 5, every two system elements are connected by the pipelines, e.g., reservoir and reservoir, reservoir and pumping station, and pumping station and water plant. In some cases, more than one reservoir or pumping station share one pipeline, leading to competition on channel flow. However, since the multi-objective optimization problem is operated on a daily time step in our study and we assume that reservoir releases or pumping station flows into the *water plant without considering the channel flow limitation, and thereby, regardless of the specific hydrologic connections between channels or pipelines.*

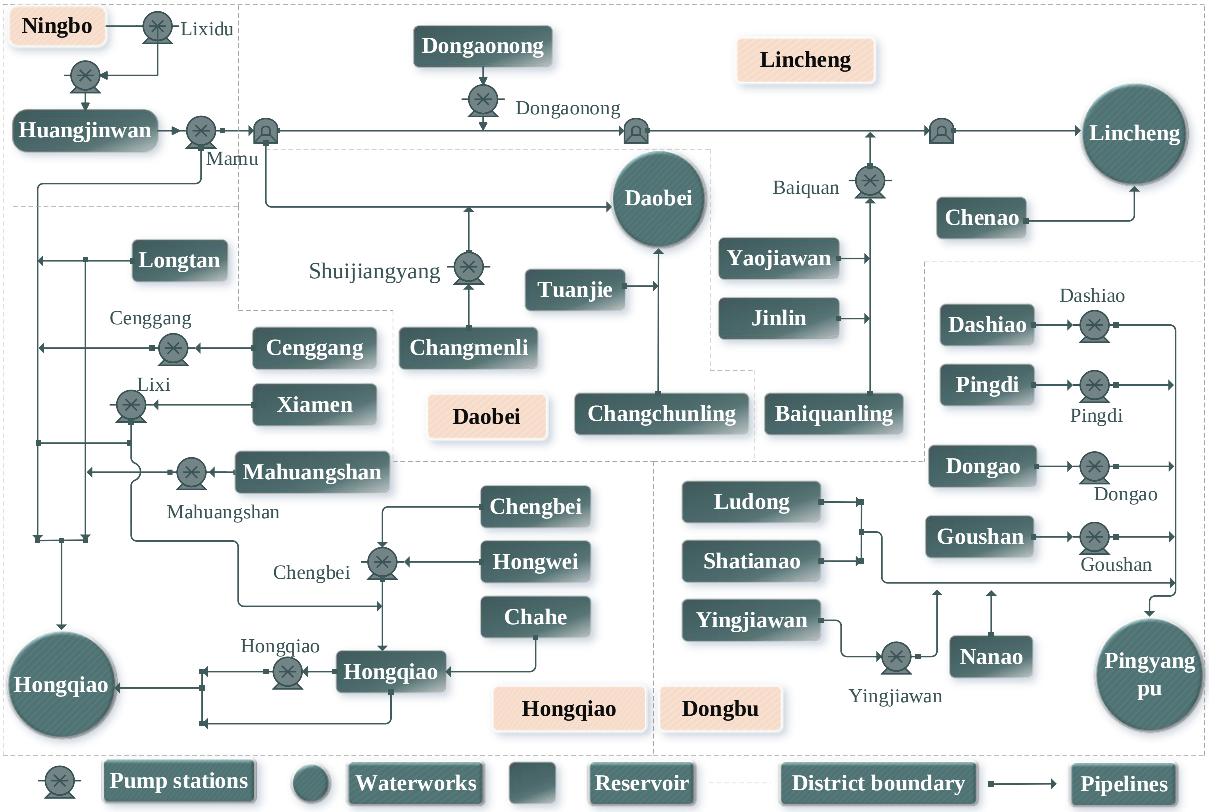

Figure 5: Schematic diagram of the Zhoushan Islands.

Technical Corrections:

(1) The “g” in (21) is left unexplained.

Authors’ response: Thanks for your comments. We have revised it. Please see Page 7, Line 168-169.

$$l(\theta)=\log\left(\sum_{k=1}^{K}\left(w_k\cdot g\left(Q|\, f_k^t,\sigma_k^2\right)\right)\right), \qquad (21)$$

where θ *is the vector of parameters* $\{w_k,\sigma_k^2,k=1,2,\ldots,K\}$. $g\left(Q|\, f_k^t,\sigma_k^2\right)$ *is Gaussian distribution function where* w_k *is the weight and* σ_k^2 *is the variance.*

(2) In Line 208, “ Γ_t is the ith policy inputs”, should it be “tth”?

Authors’ response: Thanks for your comments. We have revised it. Please see Page 10, Line 210-212.

“the k

$$u_t^k = \sum_{i=1}^{N} \omega_{i,k} \varphi_{i,k}(\Gamma_t), \qquad (32)$$

where N is the number of RBFs $\varphi(\cdot)$, Γ_t *is the policy input vectors at* t^{th} *time step including exogenous information (e.g., fore-bay water level observed or predicted inflows and precipitation).* ”

(3) In (33), ( ) Γ_{tj} is left not denoted;

Authors' response: Thanks for your comments. We have revised it. Please see Page 10, Line 213-215.

“The single RBF is defined as follows:

$$\varphi_{i,k}(\Gamma_t) = \exp\left[-\sum_{j=1}^{M} \frac{\left[(\Gamma_t)_j - c_{j,i}\right]^2}{b_{j,i}^2}\right], \qquad (33)$$

where $(\Gamma_t)_j$ *is the* jth *policy input at* t^{th} *time step and M denotes the number of policy input vectors* Γ_t, *j=1,2,...M.”*

(4) The equation in Line 282 should be indexed.

Authors' response: Thanks for your comments. We have indexed the equation as below. Please see Page 15, Line 331-332.

“In some cases, $Q_{t,j}^p$ *obtained by the RBF policies can be greater than* $Q_{j,\max}^p$, *and we will do the following step to modify* $Q_{t,n}^r$.

$$Q_{t,n}^{r\,'} = \frac{Q_{t,n}^r}{\sum_{n}^{N_j} Q_{t,n}^r} \times Q_{j,\max}^p, \qquad (53)$$

(5) Please replace the typo “fjor” in Line 520 with “for”.

Authors' response: Thanks for your comments. We have replaced the typo “fjor” with “for”. Please see Page 23, Line 573-574.

“It should be a more fair practice by using multi-criteria to do both calibration and assessment and can be interesting for future work.”

(6) The typos in (19) and (20) still remain unchanged. The sum operator should be over subscript “*k*" instead of “*i*”

Authors' response: Thanks for your comments. We are sorry for it and have revised it in the new version. Please see Page 7, Line 165.

"The posterior mean (E) and variance (V) of Q are as follows (Hoeting et al., 1999):

$$E\left[Q|D\right]=\sum_{k=1}^{K} w_k \cdot E\left[p_k\left(Q|f_k, D\right)\right]=\sum_{k=1}^{K} w_k f_k \text{ ,} \tag{19}$$

$$V\left[Q|D\right]=\sum_{k=1}^{K} w_k \cdot \left[f_k - \sum_{k=1}^{K} w_k f_k\right]^2 + \sum_{k=1}^{K} w_k \sigma_k^2 \text{ ,} \tag{20}$$