Dear Referee #1,

We highly appreciate your review and useful suggestions for our manuscript. We provide our responses to your queries below.

Kind regards, all authors

Queries by anonymous referee #1 RC1 & answers by authors are as follows:

Comment #1: Some comments in literature review could be more precisely.

- The LSTM and GRU, for example, were not only applied in few previous works (refer to Line 55 in the manuscript)

Authors' response: Thank you. We will modify Line 55 as "*LSTM and GRU networks have been successfully applied in many fields (Greff et al., 2017; Zhang et al., 2018; Jung et al., 2020; Shahid et al., 2020; Ayzel and Heistermann, 2021), and they are demonstrated to generate comparable performances. But GRU has a more straightforward structure and a higher operation speed than LSTM. Recently, many applications that assessed them together are also found in the hydrological field (Gao et al., 2020; Muhammad et al., 2020)*."

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Korea. Journal of Cleaner Production, 250, 119476, https://doi.org/10.1016/j.jclepro.2019.119476, 2020.

Muhammad A.U., Li X., Feng J. Using LSTM GRU and Hybrid Models for Streamflow Forecasting. Machine Learning and Intelligent Communications 2019. Lecture Notes of the Institute for Computer Sciences, Social Informatics and Telecommunications Engineering, Springer, 294, 510-524, https://doi.org/10.1007/978-3-030-32388-2_44, 2019.

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- The research works on impacts of forecast horizon on reservoir operation were not rare (Lines 59 and 71).

Authors' response: Thanks for your comments.

We will modify Line 59 as "*While a considerable research effort has been made to evaluate and improve the quality of streamflow forecasts (Gibbs et al., 2018; Nanda et al., 2019; Sharma et al., 2019; Van Osnabrugge et al., 2019; Feng et al., 2020; Pechlivanidis et al., 2020), how forecasts impact decision-making in the real-time reservoir operations has gradually gained researchers' attention (Goddard et al., 2010; Shamir, 2017; Anghileri et al., 2019; Alexander et al., 2020; Hadi et al., 2020), e.g., do high-quality forecasts mean improved decision?*"

We will modify Line 71 as "*There is often a mismatch between the information needed for reservoir operations and the skillful lead time of the reservoir inflow forecast (Anghileri et al., 2016). It is crucial to demonstrate the applicability and effectiveness of the forecast horizon in a forecast-based reservoir operation system (Xu et al., 2014).*"

References

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Anghileri, D., Monhart, S., Zhou, C., et al. The Value of Subseasonal Hydrometeorological Forecasts to Hydropower Operations: How Much Does Preprocessing Matter? Water Resources Research, 55(12), 10159-10178, https://doi.org/10.1029/2019WR025280, 2019.

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Sciences, 23(3), 1453-1467, https://doi.org/10.5194/hess-23-1453-2019, 2019.
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Comment #2: It is unclear how the weight matrices involved in the forecasting models (Lines: 124 and 136) were estimated, and what / which criteria were used in calibration.

Authors' response: Thanks for your comment. We will modify it in the new version. "*Both LSTM and GRU are trained based on truncated Back Propagation Through Time (BPTT) which uses a back propagation network to update the parameters in iterations (Cheng et.al., 2020). The NSE function is used as the loss function to calibrate the LSTM and GRU models*."

References

Cheng, M., Fang, F., Kinouchi, T., et al., 2020. Long lead-time daily and monthly streamflow forecasting using machine learning methods. Journal of Hydrology, 590, 125376.

Comment #3:. It is left unexplained:

- How the parameters used to define the operational policy are estimated?

Authors' response: Thanks for your comments. The parameters in the operation policy are the decision variables in our multi-objective problem, and can be estimated by NSGA-II.

- What specific hydrological variables are included in the "policy inputs"?

Authors' response: The hydrological variables in the policy inputs include fore-bay water level, observed or predicted inflows, and precipitation.

- How these "policy inputs" are related to the decision horizon?

Authors' response: Thank you. As show in Eq (32), in each operation horizon, Γ_t is the t^{th} policy inputs including exogenous information (e.g., fore-bay water level observed or predicted inflows and precipitation)

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

• How the policy could be implemented with all constraints enforced in a day-by-day practice?

Authors' response: Thank you. When using the parameterized MORDM approach to solve the multi-objective reservoir operation under uncertainty, it is indeed hard to obtain the policy that is subject to with all constraints. To avoid this potential problem, we have applied a post-processing procedure in the practice. For example, assume that $Q_{t,i,j}^{r,2}$ denotes the flow pumped by the j^{th} pump station from the i^{th} reservoir at t^{th} time step (m^3/s); $Q_{t,j}^{p}$ denotes flow through the j^{th} pump station at t^{th} time step (m^3/s), $Q_{t,j}^{p} = \sum_{i}^{N_j} Q_{t,i,j}^{r,2}$, N_j is the number of reservoirs pumped by the j^{th} pump station; $Q_{j,\max}^{p}$ denotes the upper flow boundary of the j^{th} pump station (m^3/s). In some cases, $Q_{t,j}^{p}$ can be greater than $Q_{j,\max}^{p}$, and we will do the following step $Q_{t,n,j}^{r,2\,'} = \frac{Q_{t,n,j}^{r,2}}{\sum_{n=1}^{N_j} Q_{t,n,j}^{r,2}} \times Q_{j,\max}^{p}$ to update $Q_{t,n,j}^{r,2}$. The post-processing procedure will be described in Part "3.2 Problem formulation.

• Why it is called "multi-objective" since involving only an objective (26)?

Authors' response: Thanks for your constructive comment. In this study, we focus on the multi-objective problem, and three objectives are considered in our case study. Accordingly, it should be multi-objective in this equation, and we will modify it as:

$$p_\theta^* = \arg\min_{p_\theta} \left(J_1,\ J_2, \ldots, J_M \right)_{p_\theta} \quad s.t.\ \theta \in \Theta, \quad (31)$$

where $J_1,\ J_2, \ldots, J_M$ is the objective function, and M is the number of objectives.

Moreover, to answer these above questions, we will re-organize the introduction of the Parameterized multi-objective robust decision making (MORDM).

"2.4 Parameterized multi-objective robust decision making (MORDM)

This study proposes a parameterized multi-objective robust decision-making approach to design operating policies for the multi-objective reservoir operations by combing *direct policy search (DPS) and multi-objective robust decision making (MORDM). In the parameterized MORDM, instead of using the volumes of water to be allocated as the decision variables, we prescribe decisions approximated as non-linear functions conditioned on system state variables (e.g., fore-bay water level observed or predicted inflows, and precipitation) (Giuliani et al., 2016; Quinn et al., 2017b; Salazar et al., 2017). The non-linear functions can be realized by the DPS approach. DPS is based on the parameterization of the operating policy* p_θ *and the exploration of the parameter space* Θ *to find a parameterized policy that optimizes the expected function, i.e.,*

$$p_\theta^* = \arg\min_{p_\theta} \left(J_1,\ J_2, \ldots, J_M \right)_{p_\theta} \quad s.t.\ \theta \in \Theta, \tag{31}$$

where $J_1, J_2, \ldots, J_M$ *are the multi-objective functions, M is the number of objectives, and* p_θ^* *is the corresponding optimal policy with parameters* θ^*. *Different DPS approaches have been proposed, where two nonlinear approximating networks, namely artificial neural networks (ANNs) and radial basis functions (RBFs) have become widely adopted as universal approximators in many applications (Deisenroth et al., 2013; Giuliani et al., 2016). In particular, we parameterize the operating policy as RBFs, because they have been demonstrated to be effective in solving multi-objective water resources management problems (Giuliani et al., 2014; 2015) and the* k^{th} *decision variable in the vector* u_t *(with* $k = 1, \ldots, K$*) is defined as:*

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

where N is the number of RBFs $\varphi(\cdot)$, Γ_t *is the policy inputs including exogenous information (e.g., fore-bay water level observed or predicted inflows and precipitation) and* $\omega_{i,k}$ *is the weight of the* i^{th} *RBF,* $\sum_{i=1}^{N} \omega_{i,k} = 1 \quad \omega_{i,k} > 0$. *The single RBF is defined as follows:*

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

where M denotes the number of policy inputs Γ_t *and* c_i, b_i *are the M-dimensional* *center and radius vectors of the i^th RBF, respectively. The centers of the RBF must lie within the bounded input space (Yang et al., 2017). The parameter vector θ is defined as $\theta=\left[c_{i,j,k}, b_{i,j,k}, \omega_{i,j,k}\right]$ with the number of θ is $n_{\theta}=N\times K\times\left(2\times M+1\right)$. In general, when DPS problems involve multiple objectives, they can be coupled with truly multiobjective optimization methods, such as MOEAs which allow estimating an approximation of the Pareto front in a single run of the algorithm (Giuliani et al., 2016).*

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, 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: (1) problem formulation, including the possible actions (i.e., RBF inputs and policies), performance measures, and constraints; (2) generate alternative RBF policies subjecting to all the constraints and the objectives are evaluated over stochastic inflows (i.e., BMA ensemble forecasts); (3) identify solutions with a robust rule (e.g., the principle of insufficient reason, minimax, and minimax regret) using multi-objective evolutionary algorithms (MOEAs) (Giuliani and Castelletti, 2016; Guo et al., 2020b). "

References

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Comment #4: I think this work has formulated an incomplete reservoir operation problem.

- The water balance, for instance, does not reflect the hydraulic connections shown in Figure 4. The relationships between water supply, pumping flow, inflow and discharge are not incorporated in the model.

Authors' response: Thanks for your constructive comments. All plants are supplied by the reservoirs, and we can find in Fig.4 that some reservoirs supply water without pump stations (e.g., Longtan, Changchunling, Chahe, and Nanao), while the others will be pumped by pump stations. Assume that $Q_{t,i}^{r}$ denotes flow from the i^{th} reservoir at t^{th} time step (m^3/s), in which $Q_{t,i}^{r,1}$ denotes the flow without pump station from the i^{th}

reservoir at t^{th} time step (m^3/s), $Q_{t,i,j}^{r,2}$ denotes the flow pumped by the j^{th} pump station from the i^{th} reservoir at t^{th} time step (m^3/s). W_t^s denotes the amount of water supply for plants at t^{th} time step (m^3), $W_t^s = \sum_{i=1}^{I}\sum_{t=1}^{T} Q_{t,i}^r \Delta t$, I is the total number of reservoirs; $Q_{t,j}^p$ denotes water through the j^{th} pump station at t^{th} time step (m^3/s), $Q_{t,j}^p = \sum_{i=1}^{N_j} Q_{t,i,j}^{r,2}$, N_j is the number of reservoirs pumped by the j^{th} pump station. The relationship between water supply and discharge, and that between water supply and pumping flow, are present in the description of Eqs. (38)-(39). The water balance limitation $V_{t+1,i} = V_{t,i} + \left(I_{t,i} - Q_{t,i}^r\right)\Delta t$ is mainly for reservoirs. Accordingly, we will modify the problem formulation as bellows.

"These objective functions are given as follows:

$$\text{Min} \quad f_1(x) = \left(\sum_{t=1}^{T} W_t^{n,db} - \sum_{t=1}^{T} W_t^{s,db}\right) \Big/ \sum_{t=1}^{T} W_t^{n,db} \times 100\%, \tag{34}$$

$$\text{Min} \quad f_2(x) = \left(\sum_{k=1}^{3}\sum_{t=1}^{T} W_{t,k}^{n,th} - \sum_{k=1}^{3}\sum_{t=1}^{T} W_{t,k}^{s,th}\right) \Big/ \sum_{i=1}^{3}\sum_{t=1}^{T} W_{t,k}^{n,th} \times 100\%, \tag{35}$$

$$\text{Min} \quad f_3(x) = \left(M_c^{island} + M_c^{mainland}\right) - M_r, \tag{36}$$

where f_1 and f_2 are the water deficiency ratio of Daobei Plant and the sum of the remaining three plants, respectively (%); f_3 is the net operating costs (RMB); $W_t^{s,db}$ and $W_t^{n,db}$ are the amount of water supply and demand for Daobei Plant at t^{th} time step, respectively (m^3); $W_{t,k}^{s,th}$ and $W_{t,k}^{n,th}$ are the amounts of water supply and demand for the k^{th} plant (one of the remaining three plants) at t^{th} time step, respectively (m^3); M_c^{island} and $M_c^{mainland}$ are the costs for water supply from the islands and the mainland, respectively (RMB); M_r is the revenue (RMB). The revenue can be obtained according to:

1) Operating costs for water supply from islands (M_c^{island}, RMB):

$$M_c^{island} = M_{c,1}^{island} + M_{c,2}^{island} + M_{c,3}^{island}, \tag{37}$$

$$M_{c,1}^{island} = c_1^{island} \times \sum_{t=1}^{T} W_t^{s,island} = c_1^{island} \times \sum_{i=1}^{I}\sum_{t=1}^{T} Q_{t,i}^{r,island} \Delta t, \tag{38}$$

$$M_{c,2}^{island}=c_2^{island}\times\sum_{t=1}^{T}W_t^{s,island}=c_2^{island}\times\sum_{i=1}^{I}\sum_{t=1}^{T}Q_{t,i}^{r,island}\Delta t\quad,\tag{39}$$

$$M_{c,3}^{island}=c_3^{island}\times\sum_{j=1}^{J}\sum_{t=1}^{T}\frac{Q_{t,j}^{p,island}\times P_j^{island}}{Q_{j,\max}^{p,island}}\quad,\tag{40}$$

where $M_{c,1}^{island}$, $M_{c,2}^{island}$, and $M_{c,3}^{island}$ represent the water resource fees paid to the government, water fees paid to reservoir managers, and the electricity fees in Zhoushan City, respectively (RMB); c_1^{island}, c_2^{island}, and c_3^{island} denote the constant vectors, representing the unit price of water resources, water, and electricity in Zhoushan City, respectively (RMB/m^3); Δt is the time step; i is the number of a reservoir, j is the number of a pump station, I denotes the number of reservoirs, and J denotes the number of pump stations in Zhoushan City; $W_t^{s,island}$ denotes the amount of water supply for plants at tth time step (m^3); $Q_{t,i}^{r,island}$ denotes flow from the ith reservoir at tth time step in Zhoushan City (m^3/s), in which $Q_{t,i}^{r,1,island}$ denotes the flow without pump station from the ith reservoir at tth time step (m^3/s), $Q_{t,i,j}^{r,2,island}$ denotes the flow pumped by the jth pump station from the ith reservoir at tth time step (m^3/s); P_j^{island} denotes the supporting motor power of the ith pump station (Kw); $Q_{t,j}^{p,island}$ denotes the flow through the jth pump station at tth time step (m^3/s), where $Q_{t,j}^{p,island}=\sum_{n=1}^{N_j}Q_{t,n}^{r,2,island}$, N_j is the number of reservoirs pumped by the jth pump station; $Q_{j,\max}^{p,island}$ denotes the upper flow boundary of the jth pump station in Zhoushan City (m^3/s).

2) Operating costs for water supply from the mainland ($M_c^{mainland}$, RMB)

$$M_c^{mianland}=M_{c,1}^{mainland}+M_{c,2}^{mainland}+M_{c,3}^{mainland}\ ,\tag{41}$$

$$M_{c,1}^{mainland}=c_1^{mainland}\times\sum_{t=1}^{T}W_t^{s,mainland}=c_1^{mainland}\times\sum_{t=1}^{T}Q_t^{p,mainland}\Delta t\ ,\tag{42}$$

$$M_{c,2}^{mainland}=c_2^{mainland}\times\sum_{t=1}^{T}W_t^{s,mainland}=c_2^{mainland}\times\sum_{t=1}^{T}Q_t^{p,mainland}\Delta t\quad,\tag{43}$$

$$M_{c,3}^{mainland}=c_3^{mainland}\times\sum_{j=1}^{J}\sum_{t=1}^{T}\frac{L_j+Q_{t,j}^{p,mainland}}{Q_{j,\max}^{p,mainland}}\quad,\tag{44}$$

where $M_{c,1}^{mainland}$, $M_{c,2}^{mainland}$, *and* $M_{c,3}^{mainland}$ *represent the water resources fees paid to the government, water fees paid to the river managers, and electricity fees in Ningbo City, respectively (RMB);* $c_1^{mainland}$, $c_2^{mainland}$, *and* $c_3^{mainland}$ *denote the constant vectors, representing the unit price of water resources, water, and electricity in Ningbo City, respectively (RMB/m*^{3}*);* $W_t^{s,mainland}$ *denotes the amount of water transferred from Ningbo City at t*th *time step (m*^{3}*);* $Q_t^{p,mainland}$ *denotes the flow pumped from Ningbo City at t*th *time step (m*^{3}*/s),* $Q_{t,j}^{p,mainland}$ *denotes the flow through the j*th *pump station at t*th *time step, J is the number of pump stations transferring water from Ningbo, J=2,* $Q_t^{p,mainland}=Q_{t,1}^{p,mainland}=Q_{t,2}^{p,mainland}$. L_j *denotes the length of the continental diversion pipeline using the j*th *pump station (m) and* $Q_{j,\max}^{p,mainland}$ *denotes the upper flow boundary of the j*th *pump station for water transfer (m*^{3}*/s).*

3) Revenues (M_r*, RMB)*

$$M_r = b \times \left(\sum_{t=1}^{T} W_t^{s,db} + W_t^{s,th} \right), \tag{45}$$

where b denotes the unit price of water supply revenue (RMB/m^3*).*

The optimization model is subject to the following constraints:

(1) Reservoir water balance: $$V_{t+1,i} = V_{t,i} + \left(I_{t,i} - Q_{t,i}^r \right) \Delta t, \tag{46}$$

(2) Reservoir storage limits: $$V_{t,i,\min} \le V_{t,i} \le V_{t,i,\max}, \tag{47}$$

(3) Reservoir release limits (for the reservoir that supply water without pump station): $$Q_{t,i}^r \le Q_{t,i,\max}^r, \tag{48}$$

(4) Pumping station limits: $$Q_{t,j}^p \le Q_{\max,j}^p, \tag{49}$$

where $I_{t,i}$ *is the inflow of the i*th *reservoir at t*th *time step (m*^{3}*/s);* $V_{t,i}$ *is the storage of i*th *reservoir at t*th *time step (m*^{3}*);* V_{min} *and* V_{max} *are the lower and upper storage boundaries, respectively (m*^{3}*);* $Q_{t,i,\max}^r$ *is the maximum release of the i*th *reservoir at t*th

time step (m^3/s). 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* $Q_{t,n,j}^{r,2}{}' = \frac{Q_{t,n,j}^{r,2}}{\sum_{n=1}^{N_j} Q_{t,n,j}^{r,2}} \times Q_{j,\max}^{p}$ *to update* $Q_{t,n,j}^{r,2}$ *.*

• Also, how the MORDM is related to this operational problem?

Authors' response: Thanks for your comments, we will re-organize the introduction of the parameterized MORDM approach and will describe the detailed steps how MORDM is related to the operational problem.

"*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, 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: (1) problem formulation, including the possible actions (i.e., RBF parameters) and performance measures; (2) generate alternative RBF policies subjecting to all the constraints and the objectives are evaluated over stochastic inflows; (3) identify solutions with a robust rule (e.g., the principle of insufficient reason, minimax, and minimax regret) using multi-objective evolutionary algorithms (MOEAs) (Giuliani and Castelletti, 2016; Guo et al., 2020b).*"

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https://doi.org/10.1016/j.jclepro.2020.124609, 2020b.

• The model looks like a linear programming problem that can be easily solved.

Authors' response: Thanks for your comments. There are 25 reservoirs and 16 pump stations in our multi-objective reservoir operation optimization problem. Although the objectives and constraints seem to be linear, there are some non-linear functions considered in our modelling process. For example, the relationship between the fore-bay water level and volume of reservoirs is non-linear, and normally expressed by a quadratic function. Besides, it is difficult and time consuming to assure all constraints enforced in the day-by-day practice, especially when it is operated under stochastic inflow.

Comment #5: The manuscript will benefit from more logically organizing its contents. The "Results and Discussion" are usually a part of the case studies.

Authors' response: Thank you. We will re-organize the manuscript, and put the "3.4 Results and discussion" as a part of case study, and add a part of "3.3 Model development".

Theory, models, procedures and definitions are generally presented before case studies, and some of them need more detailed introduction, including:

• How the weights in the BMA are determined (Line 320)?

Authors' response: Thank you. We will modify it as bellows.

"In this study, a log-like hood function is maximized to estimate the parameters (weight w_k *and variance* σ_k^2*) as shown in Eq (21).*

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

where θ *is the vector of parameters* $\{w_k, \sigma_k^2, k = 1, 2, ..., K\}$.

The Expectation-Maximization (EM) algorithm is used to find out the maximum likehood with a termination criterion (early stopping or a maximal iteration). As the EM proceeds, the parameters of weight w_k *and variance* σ_k^2 *are updated as follows.*

$$w_k^{(Iter)} = \frac{1}{NT}\left(\sum_{t=1}^{NT} z_k^{t^{(Iter)}}\right), \qquad (22)$$

$$\sigma_k^{2^{(Iter)}} = \frac{\sum_{t=1}^{NT} z_k^{t^{Iter}} \cdot \left(Y^t - f_k^t\right)^2}{\sum_{t=1}^{NT} z_k^{t^{Iter}}}, \qquad (23)$$

$$z_k^{t^{(Iter)}} = \frac{g\left(Q|\, f_k^t, \sigma_k^{2^{(Iter-1)}}\right)}{\sum_{k=1}^{K} g\left(Q|\, f_k^t, \sigma_k^{2^{(Iter-1)}}\right)}, \qquad (24)$$

$$l(\theta)^{(Iter)} = \sum_{t=1}^{NT} \log\left(\sum_{k=1}^{K}\left(w_k^{(Iter)} \cdot g\left(Q|\, f_k^t, \sigma_k^{2^{(Iter)}}\right)\right)\right), \qquad (25)$$

where Iter is the number of iterations. NT *is the length of calibration periods.* Y^t *and* f_k^t *are the observed and forecast streamflow at* t^{th} *time step, respectively (*m^3/s*),* $z_k^{t^{(Iter)}}$ *is the latent variable for the* k^{th} *model at* t^{th} *time in the Iter iteration.*

• How the Monte Carlo simulation method is used to generate BMA ensemble forecasts (Line 359)?

Authors' response: Thank you. We will modify it as bellows.

"We use the Monte Carlo simulation method to generate BMA ensemble forecasts. The procedure will be described as bellows.

a) Generate an integer value of i in [1, 2, ..., K] by using the corresponding probabilities [u_1*,* u_2*, ...,* u_K*]. Set the initial cumulative weight* $w_0^* = 0$ *and calculate cumulative weight* $w_i^* = w_{i-1}^* + w_i$ *for i=1,2,...,K. Create a random variable u between 0 and 1. If* $w_{i-1}^* \le u \le w_{i-1}^*$*, it indicates that the* i^{th} *model forecast would be selected and used in the next step.*

b) Generate a realization of the observation y_t *using the PDF* $g\left(y_t|\, f_k^t, \sigma_k^2\right)$.

c) Repeat the above two steps (a) & (b) for M times. M is the number of Monte Carlo simulation and set as 1000 in this study. Furthermore, 90% confidence intervals between the 5% and 95% quantities were employed to reveal the uncertainty of BMA ensemble forecasts.

• What "the previous water levels" is supposed to mean (Line 381)?

Authors' response: Thanks for your comments. The previous water levels is termed as initial fore-bay water level of reservoirs. We will modify it in the new version.

• Why the NSGA-II are still needed since we already have the operation policy determined (Line 383)?

Authors' response: Thanks for your comments. The parameters in the operation policy are the decision variable in our multi-objective problem, and can be estimated by NSGA-II. We will modify it to avoid confusion as bellows.

"*In particular, when DPS problems involve multiple objectives, they can be coupled with truly multiobjective optimization methods, such as multiobjective evolutionary algorithms (MOEAs), which allow estimating an approximation of the Pareto front in a single run of the algorithm (Giuliani et.al., 2016).*"

"*The optimization is solved at each time step (a particular forecast horizon, e.g., 1-7 days) by applying NSGA-II to search the space of decision variables and identify the islands' water allocation trajectories.*"

References

Giuliani, M., Castelletti, A., Pianosi, F., et al. Curses, tradeoffs, and scalable management: Advancing evolutionary multiobjective 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.

• How the deterministic, uncertain and observed streamflow are used in the operation (399)?

Authors' response: Thank you. We will modify it in the part "3.3 Model development" as bellows.

"*In this study, we use the parametrized MORDM approach to design operating policies for the multi-objective reservoir operations under uncertainty. The optimized operations are both regulated based on deterministic and uncertain forecast inflow. To keep fair, we perform a simulation to generate deterministic and observed ensemble* *forecasts that each deterministic and observed data are repeated 900 times, respectively. Using the uncertain streamflow forecasts (BMA, deterministic or observed ensemble forecasts) as policy inputs in the parametrized MORDM method, we can generate alternative RBF policies subjecting to all the constraints and the objectives are evaluated over stochastic inflows."*

- How the Pareto solutions are identified (Line 387)?

Authors' response: Thanks for your comments. We do not identify the Pareto solutions. In this study, we focus on assessing the overall operating performance of the multi-reservoir system under different streamflow forecast configurations (i.e., deterministic or stochastic). Accordingly, instead of evaluating the performance of each operation solution, the system operating performances are averaged over the Pareto solutions.

- Whether or not the annual revenues, costs, and water supply reliability (Line 409) are used as multiple objectives when determining the operating policy?

Authors' response: Thanks for your comments. We do not use the annual revenues, costs, and water supply reliability as the objectives. We deal with a real-time optimization problem in our study, and assume that the operating policy is determined by the stochastic short-term reservoir inflow forecasts. Accordingly, the indictors of revenues and water supply reliability over the corresponding short-term operating period are termed as the objectives. The annual revenues, costs, and water supply reliability, are just chosen as metrics to compare and assess the performance of the operating policies derived from different configurations.

- "Fake" results do not have any meaningful value, so why they are included in Table 6 in the first place (Line 428)?

Authors' response: Thank you. To the best of our knowledge, there are few inform-driven studies have clearly point out that whether or not the system operating performance is post-evaluated by the true streamflow information. The differences between Table 6 and Table 7 may provide references for beginners.

Comment #6: To the best of my understanding, the NSE was used to calibrate the forecasting models while the RMSE and MAE are also used in assessing the performance of the models. I think it should be a fairer practice by using multi-criteria to do both the calibration and assessment.

Authors' response: Thank you. Indeed, it is fairer by using multi-criteria to do both the calibration and assessment. However, in our study, we aim to identify the relationship between forecast skill and forecast-driven reservoir operation. To answer this question, five input combination scenarios are investigated and two of them are then applied to drive the multi-objective reservoir operation optimization. Accordingly, we prefer to distinguish the forecast skill of different configurations using the indictors of NSE, RMSE, and MAE, rather than improving the forecast skill. But it may be interesting to obtain forecasts when accounting for multi-criteria over both calibration and assessment period. We will add some discussion in the Part "Limitation and future work" as "*Our work suffers from some limitations, which could be overcome in future studies. One of the limitations is that the single indictor is used to calibrate the forecast models while multiple indictors are used in assessing the performance of the models. It should be a fairer practice by using multi-criteria to do both the calibration and assessment and can be interesting as a future work*."

Comment #7: Please justify why the Radial Basis Functions are used to parameterize the policy (Line 199)?

Authors' response: Thank you for your suggestion. We will modify it. "*Different DPS approaches have been proposed, where two nonlinear approximating networks, namely artificial neural networks (ANNs) and radial basis functions (RBFs) have become widely adopted as universal approximators in many applications (Deisenroth et al., 2013; Giuliani et al., 2016). In particular, we parameterize the operating policy as RBFs, because they have been demonstrated to be effective in solving multi-objective water resources management problems (Giuliani et al., 2014; 2015).*"

References

Deisenroth, M., Neumann, G., Peters, J. A Survey on Policy Search for Robotics. Foundations and Trends in Robotics, 2(1-2), 1-142, 10.1561/2300000021, 2013.

Giuliani, M., Castelletti, A., Pianosi, F., et al. Curses, tradeoffs, and scalable management: Advancing evolutionary multiobjective 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.

Giuliani, M., Herman, J., Castelletti, A., Reed, P. Many-objective reservoir policy identification and refinement to reduce policy inertia and myopia in water management. Water Resources Research. 50, 3355–3377, http://.doi.org/10.1002/2013WR014700, 2014.

Giuliani, M., Pianosi, F., Castelletti, A. Making the most of data: an information selection and assessment framework to improve water systemsoperations. Water Resources Research, 51(11), 9073–9093, http://doi.org/10.1002/2015WR017044, 2015.

Comment #8: Including the test period when minimizing the NSE (Line 285) will make it lose efficacy in assessing the model performance in future.

Authors' response: Sorry for the confusion. This should be "*As for LSSVM, we avoid overfitting by minimizing the NSE during the calibration and validation periods, while the test period is also used to assess the forecast performance*."

Technical Corrections:

Comment #1:. Please rewrite the term ($\sum_{i=1}^{K} w_k f_k$) in equation (19), which just does not make sense to me, with the f_k being a model.

Authors' response: Thanks for your comments. We will revise "model f_k" as "model forecast f_k.".

Comment #2: Please double check all the mathematical expressions.

- In equations (19) and (20), the sum should be operated over subscript "k" rather than "i".

Authors' response: Thank you. We will change "i" to "k" as bellows.

$$E\left[Q|D\right]=\sum_{i=1}^{K} w_k \cdot E\left[p_k\left(Q|f_k,D\right)\right]=\sum_{i=1}^{K} w_k f_k \quad (2)$$
,

$$V\left[Q|D\right]=\sum_{i=1}^{K} w_k \cdot \left[f_k-\sum_{i=1}^{K} w_k f_k\right]^2+\sum_{i=1}^{K} w_k \sigma_k^2 \quad (3)$$
,

• It might not be right that the subscript "k" on the left side does not appear on the right side of the equation (28)

Authors' response: Thank you. We will revise it as bellows.

$$\varphi_{i,k}(\Gamma_t)=\exp\left[-\sum_{j=1}^{M}\frac{\left[(\Gamma_t)_j-c_{j,i,k}\right]^2}{b_{j,i,k}^2}\right], \tag{4}$$

• It sounds not right to me in equation (34), where a variable without subscript "*j*" is summed over "*j*".

• It is questionable that the equation (35) does not have a subscript for the first sum operator to operate over.

• Expressing a variable subscript "*n*" in "Q_{max_n}" (Line 247) is something strange.

• Please check on all similar unprofessional expressions in (39), (42) and (43).

Authors' response: Thank you. We will modify these equations as bellows.

"

$$\text{Min} \quad f_1(x)=\left(\sum_{t=1}^{T}W_t^{n,db}-\sum_{t=1}^{T}W_t^{s,db}\right)\Big/\sum_{t=1}^{T}W_t^{n,db}\times 100\%, \tag{34}$$

$$\text{Min} \quad f_2(x)=\left(\sum_{k=1}^{3}\sum_{t=1}^{T}W_{t,k}^{n,th}-\sum_{k=1}^{3}\sum_{t=1}^{T}W_{t,k}^{s,th}\right)\Big/\sum_{i=1}^{3}\sum_{t=1}^{T}W_{t,k}^{n,th}\times 100\%, \tag{35}$$

$$\text{Min} \quad f_3(x)=\left(M_c^{island}+M_c^{mainland}\right)-M_r, \tag{36}$$

where f_1 and f_2 are the water deficiency ratio of Daobei Plant and the sum of the remaining three plants, respectively (%); f_3 is the net operating costs (RMB); $W_t^{s,db}$ and $W_t^{n,db}$ are the amount of water supply and demand for Daobei Plant at t^{th} time step, respectively (m^3); $W_{t,k}^{s,th}$ and $W_{t,k}^{n,th}$ are the amounts of water supply and demand for the k^{th} plant (one of the remaining three plants) at t^{th} time step, respectively (m^3); M_c^{island} and $M_c^{mainland}$ are the costs for water supply from the islands and the mainland, respectively (RMB); M_r is the revenue (RMB). The revenue can be obtained according to:

1) Operating costs for water supply from islands (M_c^{island}, RMB):

$$M_c^{island}=M_{c,1}^{island}+M_{c,2}^{island}+M_{c,3}^{island}, \tag{37}$$

$$M_{c,1}^{island} = c_1^{island} \times \sum_{t=1}^{T} W_t^{s,island} = c_1^{island} \times \sum_{i=1}^{I}\sum_{t=1}^{T} Q_{t,i}^{r,island} \Delta t \ , \tag{38}$$

$$M_{c,2}^{island} = c_2^{island} \times \sum_{t=1}^{T} W_t^{s,island} = c_2^{island} \times \sum_{i=1}^{I}\sum_{t=1}^{T} Q_{t,i}^{r,island} \Delta t \ , \tag{39}$$

$$M_{c,3}^{island} = c_3^{island} \times \sum_{j=1}^{J}\sum_{t=1}^{T} \frac{Q_{t,j}^{p,island} \times P_j^{island}}{Q_{j,\max}^{p,island}} \ , \tag{40}$$

where $M_{c,1}^{island}$, $M_{c,2}^{island}$, and $M_{c,3}^{island}$ represent the water resource fees paid to the government, water fees paid to reservoir managers, and the electricity fees in Zhoushan City, respectively (RMB); c_1^{island}, c_2^{island}, and c_3^{island} denote the constant vectors, representing the unit price of water resources, water, and electricity in Zhoushan City, respectively (RMB/m^3); Δt is the time step; i is the number of a reservoir, j is the number of a pump station, I denotes the number of reservoirs, and J denotes the number of pump stations in Zhoushan City; $W_t^{s,island}$ denotes the amount of water supply for plants at tth time step (m^3); $Q_{t,i}^{r,island}$ denotes flow from the ith reservoir at tth time step in Zhoushan City (m^3/s), in which $Q_{t,i}^{r,1,island}$ denotes the flow without pump station from the ith reservoir at tth time step (m^3/s), $Q_{t,i,j}^{r,2,island}$ denotes the flow pumped by the jth pump station from the ith reservoir at tth time step (m^3/s); P_j^{island} denotes the supporting motor power of the ith pump station (Kw); $Q_{t,j}^{p,island}$ denotes the flow through the jth pump station at tth time step (m^3/s), where $Q_{t,j}^{p,island} = \sum_{n=1}^{N_j} Q_{t,n}^{r,2,island}$, N_j is the number of reservoirs pumped by the jth pump station; $Q_{j,\max}^{p,island}$ denotes the upper flow boundary of the jth pump station in Zhoushan City (m^3/s).

2) Operating costs for water supply from the mainland ($M_c^{mainland}$, RMB)

$$M_c^{mianland} = M_{c,1}^{mainland} + M_{c,2}^{mainland} + M_{c,3}^{mainland} \ , \tag{41}$$

$$M_{c,1}^{mainland} = c_1^{mainland} \times \sum_{t=1}^{T} W_t^{s,mainland} = c_1^{mainland} \times \sum_{t=1}^{T} Q_t^{p,mainland} \Delta t \ , \tag{42}$$

$$M_{c,2}^{mainland} = c_2^{mainland} \times \sum_{t=1}^{T} W_t^{s,mainland} = c_2^{mainland} \times \sum_{t=1}^{T} Q_t^{p,mainland} \Delta t \ , \tag{43}$$

$$M_{c,3}^{mainland} = c_3^{mainland} \times \sum_{j=1}^{J}\sum_{t=1}^{T} \frac{L_j + Q_{t,j}^{p,mainland}}{Q_{j,\max}^{p,mainland}}, \quad (441)$$

where $M_{c,1}^{mainland}$, $M_{c,2}^{mainland}$, and $M_{c,3}^{mainland}$ represent the water resources fees paid to the government, water fees paid to the river managers, and electricity fees in Ningbo City, respectively (RMB); $c_1^{mainland}$, $c_2^{mainland}$, and $c_3^{mainland}$ denote the constant vectors, representing the unit price of water resources, water, and electricity in Ningbo City, respectively (RMB/m^3); $W_t^{s,mainland}$ denotes the amount of water transferred from Ningbo City at t^{th} time step (m^3); $Q_t^{p,mainland}$ denotes the flow pumped from Ningbo City at t^{th} time step (m^3/s), $Q_{t,j}^{p,mainland}$ denotes the flow through the j^{th} pump station at t^{th} time step, J is the number of pump stations transferring water from Ningbo, $J=2$, $Q_t^{p,mainland} = Q_{t,1}^{p,mainland} = Q_{t,2}^{p,mainland}$. L_j denotes the length of the continental diversion pipeline using j^{th} pump station (m) and $Q_{j,\max}^{p,mainland}$ denotes the upper flow boundary of the j^{th} pump station for water transfer (m^3/s).

3) Revenues (M_r, RMB)

$$M_r = b \times \left(\sum_{t=1}^{T} W_t^{s,db} + W_t^{s,th} \right), \quad (45)$$

where b denotes the unit price of water supply revenue (RMB/m^3).

The optimization model is subject to the following constraints:

(1) Reservoir water balance: $V_{t+1,i} = V_{t,i} + \left(I_{t,i} - Q_{t,i}^r \right) \Delta t$, *(46)*

(2) Reservoir storage limits: $V_{t,i,\min} \le V_{t,i} \le V_{t,i,\max}$, *(47)*

(3) Reservoir release limits (for the reservoir that supply water without pump station): $Q_{t,i}^r \le Q_{t,i,\max}^r$, *(48)*

(4) Pumping station limits: $Q_{t,j}^p \le Q_{\max,j}^p$, *(49)*

where $I_{t,i}$ is the inflow of the i^{th} reservoir at t^{th} time step (m^3/s); $V_{t,i}$ is the storage of i^{th} reservoir at t^{th} time step (m^3); V_{min} and V_{max} are the lower and upper storage boundaries, respectively (m^3); $Q_{t,i,\max}^r$ is the maximum release of the i^{th} reservoir at t^{th}

time step (m^3/s). 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 $Q_{t,n,j}^{r,2}{}' = \frac{Q_{t,n,j}^{r,2}}{\sum_{n=1}^{N_j} Q_{t,n,j}^{r,2}} \times Q_{j,\max}^{p}$ to update $Q_{t,n,j}^{r,2}$."

Comment #3: Please do not omit subscripts in mathematical symbols. And for all the definitions of math symbols, all the subscripts in any symbol should appear in its definition.

Authors' response: Thank you. We will double check all the subscripts in mathematical symbols.