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DOI
10.1007/s11269-019-02284-x

Publication date
2019

Document Version
Accepted author manuscript

Published in
Water Resources Management

Citation (APA)
Tian, X., Guo, Y., Negenborn, R. R., Wei, L., Lin, N. M., & Maestre, J. M. (2019). Multi-scenario Model Predictive Control based on genetic algorithms for level regulation of open water systems under ensemble forecasts. *Water Resources Management*, *33*(9), 3025-3040. https://doi.org/10.1007/s11269-019-02284-x

Water Resources Management manuscript No.
(will be inserted by the editor)

Multi-Scenario Model Predictive Control Based on Genetic Algorithms for Level Regulation of Open Water Systems under Ensemble Forecasts

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Received: date / Accepted: date

Abstract Operational water resources management needs to adopt operational strategies to re-allocate water resources by manipulating hydraulic structures. Model Predictive Control (MPC) has been shown to be a promising technique in this context. However, we still need to advance MPC in the face of hydrological uncertainties. This study makes the first attempt to combine Multi-Scenario MPC (MSMPC) with a Genetic Algorithm (GA) to find Pareto optimal solutions for a multi-scenario operational water resources management problem. Then three performance metrics are adopted to select the solution to be implemented. In order to assess the performance of the proposed approach, a case study of the North Sea Canal in the Netherlands is carried out, in which ensemble discharge forecasts are used. Compared with classic MSMPC approaches that deal with uncertainty by the weighted sum approach, GA-MSMPC can better fulfill management goals although it may also be computationally

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expensive. With the rapid development of multi-objective evolutionary algorithms, our study suggests the potential of GA-MSMPC to deal with a wide range of operational water management problems in the future.

Keywords Model Predictive Control · genetic algorithms · multiple scenarios · water level regulation · ensemble forecasts

1 Introduction

To fulfill water resources planning and management, hydraulic structures are designed and operated in many modern water systems (Loucks et al., 2005). Water resources planning (WRP) usually deals with problems with long-term forecast horizons, e.g., years or decades, which can be solved either by simulation-based or optimization-based decision-making approaches. Key issues, such as trade-offs between conflicting objectives, uncertainties, robustness, and adaptability are commonly included in WRP problems (Vogel et al., 2015). Nevertheless, the speed of the decision-making process is often of the least importance. On the other hand, water resources management (WRM), which deals with operations of hydraulic structures, cannot neglect computational efficiency because structures are often manipulated hourly or sub-hourly. To that end, a family of real-time control (RTC) methodologies has been developed for water systems, based on systems and control theory (Malaterre et al., 1998; Schuurmans et al., 1999).

Although some rationales and principles differ in these two branches of water resources, there are still relevant commonalities. First, both planning and management need to face the multi-objective nature of challenges in regard to water resources (Reed et al., 2013; Beh et al., 2015). Second, the uncertainty plays a critical role in decision-making in both branches (Vogel et al., 2015; Maier et al., 2016). Specifically, while WRP usually needs to consider a large range of uncertainties that may influence behaviors of the system in the distant future (Matrosov et al., 2015; Walsh et al., 2016), WRM mainly focuses on the uncertainty derived from system inputs and disturbances, assuming that the system settings do not change significantly in the near future (Raso et al., 2014; Ficchì et al., 2016). Third, optimization-based algorithms are currently the most popular and effective tool to solve problems in both branches.

Multi-objective Evolutionary Algorithms (MOEAs) are one of the primary breakthroughs in the last five years in water resources (Reed et al., 2013; Maier et al., 2014; Giuliani et al., 2016). For examples, popular algorithms include the non-dominated sorting genetic algorithm II (NSGA-II) (Deb et al., 2002), strength-Pareto evolutionary algorithm II (SPEA-II) (Kim et al., 2004), and Multi-objective Particle Swarm Optimization (MOPSO) (Coello Coello and Lechuga, 2002). The MOEAs, aiming to find a Pareto front from conflicting objectives, have been widely applied to WRP problems (see (Reed et al., 2013; Maier et al., 2014) for a comprehensive review). Meanwhile, the RTC also entered a new era using the optimization-based methodology – Model Predictive Control (MPC) – to deal with large-scale and distributed problems (Maestre and Negenborn, 2014; Maciejowski, 2002; Camacho and Bordons, 1999). More importantly, MPC is a proactive approach that uses water system models and hydrological forecasts to anticipate future states and maximize the performance of operations. As a result, MPC has shown satisfactory performance in multiple WRM applications, including irrigation and drainage canal control (Negenborn et al., 2009), drinking and sewer networks (Joseph-Duran et al., 2014; Grosso et al., 2014), and reservoir operations and flood defense (Tian et al., 2014; Raso and Malaterre, 2016; Galelli et al., 2014; Ficchì et al., 2016).

To represent the uncertainty involved in an RTC-WRM problem, Ensemble Forecasts (EFs) are usually used. Such EFs can be generated from statistics of historical time-series (Loucks et al., 2005; Katz et al., 2002). However, decision-making with EFs is still not well addressed with respect to RTC. Past studies either used Multi-Scenario MPC (MSMPC) (van Overloop et al., 2008; Tian et al., 2017) or tree-based MPC (Raso and Malaterre, 2016; Raso et al., 2014; Maestre et al., 2013), both of which are scenario-oriented. In other words, the decision is inclined to one single scenario or the average of all the scenarios. Inspired by the successful application of MOEAs in WRP, this study attempts to apply NSGA-II, as one of the most efficient EAs, to cope with multiple scenarios in RTC-WRM. It should also be noted that very few studies use EAs in the context of RTC except a recent one (Vermuyten et al., 2018), which proposed a reduced form to find discrete solutions but only considered deterministic scenarios. In this study, we propose an approach that takes each scenario into account in an individual optimization problem and finds a set of non-dominated solutions for all scenarios. Finally, a score matrix, which considers the overall performance, is implemented to determine the final solution.

This paper is organized as follows. Section 2 describes the frameworks of MSMPC and GA-MSMPC that can be applied to WRM problems with ensemble streamflow forecasts. In Section 3, both approaches are tested on a water level regulation problem for a case study – the North Sea Canal in the Netherlands. Performances of both approaches are shown in Section 4. Section 5 further discusses the two approaches and their limitations. Conclusions are presented in Section 6.

2 Solving Multi-Scenario WRM Problems by MSMPC and GA-MSMPC

This section describes the frameworks of MSMPC and GA-MSMPC and the way to apply them to WRM problems, with the given ensemble streamflow forecasts.

2.1 Generic MPC Applied to Open Water Systems

In this section, we briefly introduce the rationale of generic MPC applied to practical water resources management problems of open water systems. For detailed formulations and descriptions, see (van Overloop, 2006a; Tian, 2015).

As an optimization-based control technique, MPC is composed of three main components: an objective function that contains management goals (Eq. 1), an internal model calculating system dynamics (Eq. 2), and constraints representing physical and operational limits (Eq. 3). The formulation of an MPC controller at every time instant is commonly given by (Maciejowski, 2002):

$$\min_{u(1),\ldots,u(N_\mathrm{p})} J(k) = \sum_{k=1}^{N_\mathrm{p}} f(x(k+1),u(k)) \tag{1}$$

subject to

for $k = 1,\ldots,N_\mathrm{p}$

$$x(k+1) = s(x(k),u(k),d(k)) \tag{2}$$

$$g(x(k+1),u(k)) \leq b(k) \tag{3}$$

where $N_{\mathrm{p}} \in \mathbb{R}^{+}$ is the length of the forecasting horizon, $x \in \mathbb{R}^{n}$ is the state vector comprised of water levels and flows with the initial condition $x(1)$, $u \in \mathbb{R}^{m}$ is the control variable vector which is the change in structure flows, $d \in \mathbb{R}^{n}$ is the system disturbance vector composed of exogenous (non-controllable) variables, $f : \mathbb{R}^{n+m} \to \mathbb{R}$ is the cost function derived from management goals, $s : \mathbb{R}^{n+m+n} \to \mathbb{R}^{n}$ is the function describing system dynamics, $g : \mathbb{R}^{(n+m)\times l} \to \mathbb{R}^{l}$ and $b(k) \in \mathbb{R}^{l}$ are the constraint function and constraint vector, respectively. The feasible optimal or sub-optimal solution is found by solving the optimization problem (1)-(3). Note that the formulation of the optimization problem is defined at every control step and MPC works in a receding-horizon way. In other words, the MPC controller only adopts the first control action of the control variable vector, which corresponds to the current time step. When moving to the next step with new measurements and new forecasts, the optimization problem (1)-(3) is to be solved again and only the first control action of the control variable vector is applied at the next step.

To tackle a problem involving setpoints, the cost function f in (1) is often expressed in a quadratic form as (van Overloop, 2006b):

$$f(x(k+1),u(k)) = \begin{bmatrix} x(k+1)-r(k+1) \\ u(k) \end{bmatrix}^{\mathrm{T}} \begin{bmatrix} Q & 0 \\ 0 & R \end{bmatrix} \begin{bmatrix} x(k+1)-r(k+1) \\ u(k) \end{bmatrix} \tag{4}$$

where $Q \in \mathbb{R}^{n\times n}$, and $R \in \mathbb{R}^{m\times m}$ are positive and definite matrices that implement quadratic penalties on states and control variables, and $r \in \mathbb{R}^{n}$ is the setpoint vector. In this study, the values of Q and R are determined by the Maximum Allowed Value Estimate (van Overloop, 2006b, Chapter 3).

Although the Saint-Venant equations describe the dynamics of open water systems well, we often consider its simplified and discretized form for computational efficiency when applying MPC (van Overloop, 2006b). In this study, we adopt a numerical scheme developed by (Stelling and Duinmeijer, 2003; Xu, 2013) to describe the system dynamic function s in Eq. (2) as follows:

$$x(k+1) = Ax(k) + B_u u(k) + B_d d(k) \tag{5}$$

where the matrices $A \in \mathbb{R}^{n\times n}$, $B_u \in \mathbb{R}^{n\times m}$ and $B_d \in \mathbb{R}^{n\times l}$ have cofficients derived from the discretization of the Saint-Venant equations. Readers can find the detailed elements of these three matrices in Appendix B of (Xu, 2013). Note that the MPC formulation is deterministic if the evolution of d (or x) in Eq. (2) is known while it becomes stochastic if it is uncertain.

2.2 Multi-Scenario MPC with EFs

To characterize plausible future states owing to stochastic hydrological and meteorological processes, EFs are commonly used. Each time series of EFs presumably carries that likelihood of occurrence in forecasting models. Based on the likelihood, Multi-Scenario MPC (MSMPC) sums the weighted objective functions of all scenarios (i.e. EFs) into a single one as follows (van Overloop et al., 2008):

$$\begin{aligned} &\min_{u(1),\ldots,u(N_{\mathrm{p}})} \sum_{i=1}^{N_{\mathrm{s}}} p_i J_i(k) = \sum_{i=1}^{N_{\mathrm{s}}} p_i \left(\sum_{k=1}^{N_{\mathrm{p}}} f_i(x_i(k+1),u(k)) \right) \\ &\text{subject to} \\ &\text{for } k = 1,\ldots,N_{\mathrm{p}}, i = 1,\ldots,N_{\mathrm{s}} \\ &x_i(k+1) = Ax_i(k) + B_u u(k) + B_d d_i(k) \\ &g(x_i(k+1),u(k)) \le b(k) \end{aligned} \tag{6}$$

where the subscript $i \in \mathbb{R}^+$ represents the i-th scenario, $p_i \in \mathbb{R}$ is the likelihood of occurrence for i-th scenario, and $N_\mathrm{s} \in \mathbb{R}^+$ is the number of scenarios. Note that we obtain a collection of states x_i because of different forecasting disturbances d_i. However, the control vector u is identical in all scenarios, which implies that we can make only one decision at every decision-making moment.

By both merging multi-objective optimization problems and solving a single-objective optimization problem, MSMPC gains efficiency to a large extent for WRM problems (Tian et al., 2017). However, the way to define a weight is strongly subjective, which requires a sound forecasting model to estimate the likelihood of occurrences. In addition, we lose the chance to find Pareto-optimal solutions and make a decision by trading off multiple plausible scenarios.

2.3 GA-MSMPC with EFs

Alternatively, this paper proposes a GA-based MSMPC (GA-MSMPC) method to cope with the situation when we need to deal with different scenarios. We formulate an individual optimization problem with respect to each scenario. In other words, for N_s scenarios, we build N_s-objective optimization problems as follows:

$$
\begin{array}{l}
\left\{ \min\limits_{u(1),\,\ldots\,,u(N_\mathrm{p})} \sum\limits_{k=1}^{N_\mathrm{p}} f_1(x_i(k+1),u(k)),\ldots, \min\limits_{u(1),\ldots,u(N_\mathrm{p})} \sum\limits_{k=1}^{N_\mathrm{p}} f_{N_\mathrm{s}}(x_i(k+1),u(k)) \right\} \\
\text{subject to} \\
\text{for } k=1,\ldots,N_\mathrm{p}, i=1,\ldots,N_\mathrm{s} \\
x_i(k+1) = Ax_i(k) + B_u u(k) + B_d d_i(k) \\
g(x_i(k+1),u(k)) \leq b(k)
\end{array} \tag{7}
$$

where the internal model and the constraint are still the same as those of Eq. (6).

This multi-objective optimization problem can be solved by a family of evolutionary algorithms. Our study adopts one of the most popular algorithms – the Non-Dominated Sorting Genetic Algorithm (NSGA-II) – for solving the multi-objective optimization problem (7). The NSGA-II is a fast and elitist MOEA algorithm (Deb et al., 2002), which potentially meets the requirement of computational efficiency in RTC problems.

The NSGA-II approach has greatly improved the traditional NSGA approach by incorporating elitism, excluding a specific sharing parameter, and decreasing the computational complexity from a cubic order of the population size to a quadratic order (Deb et al., 2002). The NSGA-II approach generates offspring using a specific type of crossover and mutation and then selects the next generation according to nondominated-sorting and crowding distance comparison. The key steps to apply NSGA-II to a multi-objective optimization problem are as follows (Deb et al., 2002):

i) Select parents from the population by using binary tournament selection based on a predefined fitness (rank) function, crowding distance, and constraints. Note the crowding distance measures the closeness between a given individual and the rest. Therefore, large crowding distance implies a more diverse distribution of the selection.
ii) Generate offspring from selected parents by using crossover and mutation operators.
iii) Sort the current population and offspring based on a non-domination rule. Eventually, we obtain N_l individuals, corresponding to the Pareto optimal solutions. We denote $U = \left\{ \boldsymbol{u}_1, \ldots, \boldsymbol{u}_{N_\mathrm{l}} \right\}$ as the set of all Pareto optimal solutions where the bold symbol represents the solution vector, i.e., $\boldsymbol{u}_\mathbf{1} = [u_1(1), \ldots, u_1(N_\mathrm{p})]^\mathrm{T}$.

2.4 Selecting a Solution from Pareto Optimal Solutions

Most decision-making techniques, including real-time control, only need one solution for implementation. To select the solution from the Pareto optima set, we first calculate a matrix (Eq. 8) to represent the cost of a given cost function based on each Pareto optimal solution.

$$\begin{bmatrix} f_1(u_1) & & f_{N_s}(u_1) \\ \vdots & \ddots & \vdots \\ f_1(u_{N_l}) & & f_{N_s}(u_{N_l}) \end{bmatrix} \tag{8}$$

The i-th column of matrix (8) represents a vector of costs when substituting the Pareto optimal solution vector $\{\boldsymbol{u}_1, ..., \boldsymbol{u}_{N_l}\}$ into the objective function f_i while the j-th row represents a series of costs when substituting $\boldsymbol{u}_j$ into functions f_1 to f_{N_s}. We then use the following metrics to determine the solution that leads to a desired performance.

2.4.1 Minimax Criterion

The minimax criterion for a minimization problem is equivalently the maximin criterion for a maximization problem. This approach targets the worst outcome by minimizing the maximum possible costs, which is usually adopted when the decision maker expects to avoid the worst situation and achieve robustness. Mathematically, it can be expressed as follows (Giuliani et al., 2016):

$$\min_i (\underbrace{\max_j (f_j(u_i))}_{\text{worst outcome w.r.t } u_i}) \tag{9}$$

2.4.2 Minisum Criterion

The minisum, or equivalently minimean, considers the overall performance by calculating the total outcome of all N_s scenarios for a give solution. This approach is usually adopted when the solution is expected to have a generally good performance in all scenarios. Its mathematical form can be expressed as follows:

$$\min_i (\underbrace{\sum_j (f_j(u_i))}_{\text{total outcome w.r.t. } u_i}) \tag{10}$$

2.4.3 Score Matrix

We also propose a score matrix, which is a mini-weighted-sum metric, to assess the general performance of a given solution in all scenarios. By ranking the costs of the i-th column from lowest to highest, we first calculate the t-th percentiles. We then define a score matrix Δ whose element $\delta(i, j)$ is expressed as follows:

$$\delta(i,j) = \begin{cases} 1 & \text{if } f_j(u_i) <= {F_j}^{15\text{th}} \\ 0.25 & \text{if } {F_j}^{15\text{th}} < f_j(u_i) <= {F_j}^{30\text{th}} \\ 0 & \text{if } {F_j}^{30\text{th}} < f_j(u_i) <= {F_j}^{70\text{th}} \\ -0.25 & \text{if } {F_j}^{70\text{th}} < f_j(u_i) <= {F_j}^{85\text{th}} \\ -1 & \text{if } f_j(u_i) > {F_j}^{85\text{th}} \end{cases} \tag{11}$$

where F_j^{t-th} is the t-th percentile of the column vector $\{f_j(u_1),...,f_j(u_{N_1})\}$ sorted from the minimum to the maximum. Specifically, the score matrix Δ implies the degree to which all Pareto optimal solutions perform with respect to each objective. In other words, the contribution of a solution to each objective is considered. If one solution leads to the minimum, it gains a score of 1, while if another solution leads to a cost which is larger than most other costs, it loses a score of 1. If its performance is still smaller than the 30th percentile, it gains 0.25. In doing so, the sorted solutions that are the best in some scenarios (with a score of 1) and not bad in some other scenarios (with a score of 0.25) are to be adopted.

Finally, by summing the matrix Δ row by row and multiply it by the likelihood of occurrence, we obtain the total performance index of every Pareto optimal solution on all objectives, as shown in Eq. (12). In other words, the final solution is the one that has the highest total score, considering all scenarios.

$$\max_i \left(\begin{bmatrix} \sum_{j=1}^{N_s} p_1 \delta(1,j) \\ \vdots \\ \sum_{j=1}^{N_s} p_{N_s} \delta(N_l,j) \end{bmatrix} \right) \tag{12}$$

3 Case Study

To compare the performances of MSMPC and GA-MSMPC for an RTC-WRM under uncertainty, we conducted a case study based on the North Sea Canal in the Netherlands, which is a major navigation canal connecting the North Sea, Amsterdam, and central Europe. The main controllable structure in this area is a pumping station at the river mouth IJmuiden, whose capacity of 260 m^3/s is one of the largest in Europe. We chose a wet period of sixty days in 2003 as the test period. Water flowing into the North Sea Canal from rivers and canals were resampled. We retrieved historical data from the Dutch live web water service[1] and generated twenty replicates at each simulation step. Using the mean value and the standard deviation of the historical time series, a Gaussian distribution was considered for resampling. It should be noted that we do not aim to show how accurately we can forecast the future. Instead, the concern of this study is to show how different future scenarios can be embedded and tackled in the proposed approach. The twenty inflow replicates are shown in Fig. 1-(a). Although twenty plausible scenarios are all considered for decision-making, there is only one possibility that may happen in reality and will impact our decisions. Therefore, three scenarios are selected as the actual case to assess the performance of control actions. Scenario 1 is an event with the highest discharge, Scenario 2 has stochastically high and low discharges, and Scenario 3 has the lowest discharge, as shown in Fig. 1-(b).

Two management goals were considered in our water level regulation problem:

(a) Safety. Water levels of the canal is expected to be regulated between -10 m and 3.5 m to ensure the safety. This safety requirement can be met by setting a constraint in two optimization problems (6) and (7).
(b) Navigation. Water level is expected to be maintained at a predetermined target level, 0 m. Low water levels result in an increased number of barges and ships for the same load of goods, and an increased total waiting time at locks as well. High water levels cause more

[1] `https://waterinfo.rws.nl.`

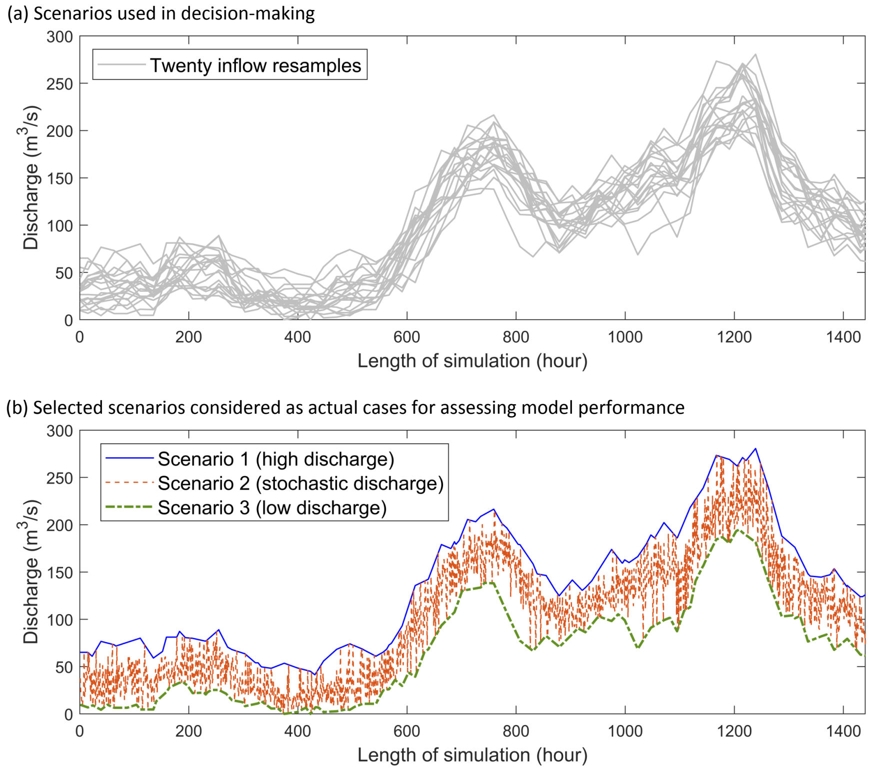

Fig. 1 (a) Twenty resampled flows into the North Sea Canal. The test period is sixty days, equivlantly 1440 hours. (b) Three selected scenarios for assessing model performance.

frequent operations of drawbridges and risks at harbors. This navigation requirement can be met by setting a setpoint in the objective function. In our study, water level outside the range of -1 m and 1 m is regarded as a violation of navigation requirements.

The MSMPC and GA-MSMPC problems with multiple scenarios were run on a 3.50 GHz Intel®Core™2 Quad processor computer. The multi-objective optimization problems were coded in Matlab (Mathworks, 2018) and solved by the interior-point method in MSMPC and NSGA-II in GA-MSMPC, respectively. The algorithms for solving the optimization problem were embedded in the water system simulator SOBEK 2.13 (Deltares, 2013), with a specific real-time module to take in user-defined routines. SOBEK 2.13 is a software package for river management, using the De Saint-Venant equations as its basic governing equations. All the parameters used in the simulation are shown in Table 1.

4 Results

In this section, we examine the regulated water level in three selected scenarios by using the four proposed methods, namely, MSMPC, GA-MSMPC with the minimax criterion (GA_max), GA-MSMPC with the minisum criterion (GA_sum), and GA-MSMPC with the score matrix (GA_score). The controlled water levels of three selected scenarios are shown

Table 1 Simulation parameters.

Parameters	**Symbols**	**Values**
Storage capacity of North Sea Canal	S	$3.1\cdot10^7$ (m^3)
Number of scenarios	N_s	20
Control time step	T_c	1 (h)
Forecast horizon	N_p	6 (h)
Simulation horizon	N	1440 (h)
Setpoint of the water level	r	0 (m ASL)
Quadratic penalty on u	R	$1/260$
Quadratic penalty on the target level r	Q	10000
Occurrence likelihood of $i-$th scenario	p_i	5%
Initial population in GA	P	70

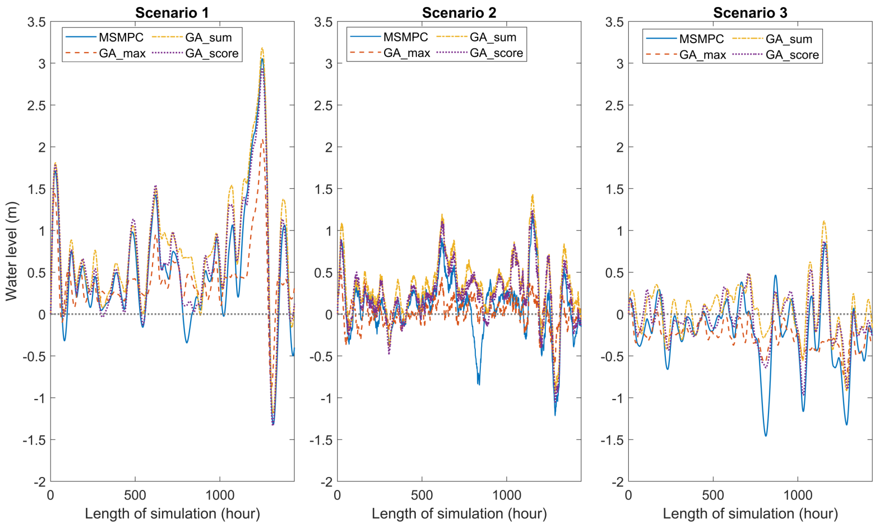

Fig. 2 Water levels of the canal using MSMPC and GA-MSMPC for three selected scenarios. Note GA_max, GA_sum, and GA_score stand for the GA-MSMPC method using the minimax, minisum, and score matrix criteria, respectively.

in Fig. 2 and the overall performance is also shown in a cumulative probability distribution diagram (Fig. 3).

4.1 Scenario 1

In Scenario 1, in which the inflow discharge is very high (even higher than the pump capacity at some steps), a method that can lower the water level to the greatest extent is desired. Among all the proposed methods, GA_max shows the best performance, as shown in Fig. 2 (Scenario 1). During several high discharge periods, for example, between steps 1200 and 1300, only GA_max can regulate the water level below 2 m, much lower than that of other methods. MSMPC shows the second best performance. It pumps water out ahead of the high discharge to create storage space, for example, at steps 800 and 1100. However, the decision-making in MSMPC takes the average of all twenty scenarios into account so

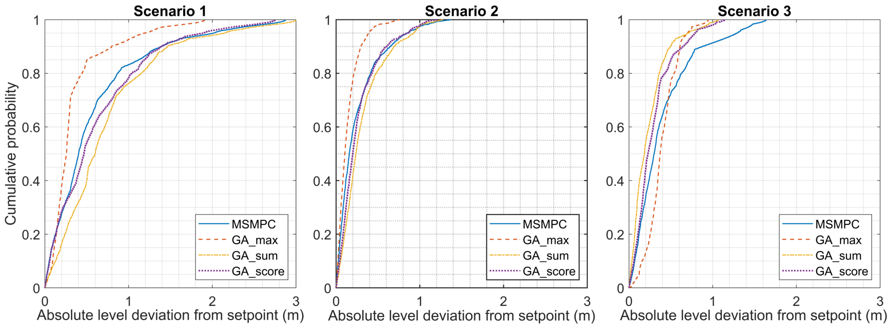

Fig. 3 Cumulative probability distribution of water levels of the canal using MSMPC and GA-MSMPC for three selected scenarios.

the controller is not able to avoid the worst case, resulting in a high water level of 3 m at step 1200. Besides, both GA_sum and GA_score do not show a satisfactory performance in Scenario 1. Similar to MSMPC, the decision-making in GA_sum and GA_score focuses on the overall performance of all scenarios, rather than the worst-case scenario. In other words, they are not good methods to deal with EFs if the actual case is a high-discharge event.

In Fig. 3 (Scenario 1), we can see that GA_max significantly outperforms other methods although they all meet the first management goal (safety). Regarding the second management goal (navigation), 93% of all steps in GA_max can regulate the water level within 1 m from the setpoint. However, only 84%, 80%, and 76% can meet the same target in MSMPC, GA_score, and GA_sum, respectively.

4.2 Scenario 2

Scenario 2 has stochastic inflows. Therefore, a method that detects and controls the variation of the system state is desired. As shown in Fig. 2 (Scenario 2), GA_max still has the best performance among all the methods, which avoids the sudden change in water levels and keeps them close to the setpoint well. The remaining methods do not preform satisfactorily. MSMPC overacts to the high discharge, lowering the water level to nearly -1 m at step 800 and jeopardizing the navigation. GA_sum and GA_score show a similar problem to Scenario 1. They are insensitive to the high discharge, whose water level is about 1 m higher than that of GA_max, for instance, at step 1100.

Fig. 3 (Scenario 2) shows that the performances of these four methods are similar to that of Scenario 1. In other words, GA_max greatly outperforms the other methods while GA_sum has the worst performance. It should be noted that although all four methods have different performances, they all meet the navigation goal during more than 97% of the simulation.

4.3 Scenario 3

Scenario 3 has the lowest discharge of all the scenarios, which implies the system needs to deal less with the high discharge nuisance. Instead, a method that can regulate the water level to be close to the setpoint is desired. Fig. 2 (Scenario 3) shows that GA_sum can regulate the water level near the reference level and that most of the level deviations are positive (i.e. the actual water level is higher than the reference level) while the remaining three methods tend to have negative level deviations. GA_max, which shows the best performance in Scenarios 1 and 2, does not remain the same in Scenario 3. For instance, GA_max results in the largest negative level deviation between steps 400 and 700. This is because a decision focusing on the high discharge (as the worst case), rather than actual low discharge, is made in GA_max. We can also see that MSMPC over-estimates the inflow discharge and lowers the water level to -1.5 m approximately, showing the worst performance of four methods.

Additionally, Fig. 3 (Scenario 3) further shows the overall performance of the whole simulation. GA_sum outperforms other methods in terms of the controlled water level, being lower than 0.7 m during 95% of the simulation. GA_max also does best in terms of the controlled water level higher than 0.7 m. In general, GA_score is the second best method, whose overall performance is slightly lower than that of GA_sum and much higher than that of MSMPC.

5 Discussion

In this section, we further discuss the performance, computational efficiency, and limitation of MSMPC and GA-MSMPC.

5.1 MSMPC versus GA-MSMPC for RTC problems

The simulation of three scenarios shows rather different results, although they all use the same information in decision-making. The difference occurs due to two factors: (i) which scenario being the actual case is differently assumed; (ii) solutions are selected following different criteria at each step. Those two factors can significantly impact the performance of the decision. In addition, MPC works in a receding-horizon fashion which implies that the system state, decision, and disturbances are updated at each step (hourly in our case) and in a closed loop. As a result, the accumulative change in water levels can be fairly different by using multiple methods (e.g., see Fig. 2 and Fig. 3).

MSMPC is currently one of the most commonly used methods to deal with multiple scenarios in RTC-WRM problems. Its decision is made upon 'the average (second-order) impact of all scenarios'. In other words, a high-impact event (i.e., a high-discharge scenario as in our case) can possibly drive the average impact away and over-estimate the consequence. However, it is still a universal method that can be used for all kinds of scenarios with an intermediate outcome. As shown in Fig. 4, which counts the steps for a given method outperforming other methods, MSMPC shows insignificantly different performances for three scenarios. It is not the best nor the worst among all the four methods.

GA_max is a very effective method that can avoid negative consequences caused by high-impact events. It achieves the best performance for Scenarios 1 and 2. Therefore, the method is recommended for decision-making if negative consequences are likely to occur and expected to be avoided. However, since it is a method focusing on the worst-case scenario, we also need to pay attention to its over-estimation if the high-impact event does not actually happen, such as Scenario 3. In this case, the performance of GA_sum is rather low.

GA_sum is a method that considers the overall performance of all solutions. In other words, its decision is made upon 'the average impact of all solutions'. GA_sum shows the best performance when only low-impact events occur (Scenario 3) but the worst in terms

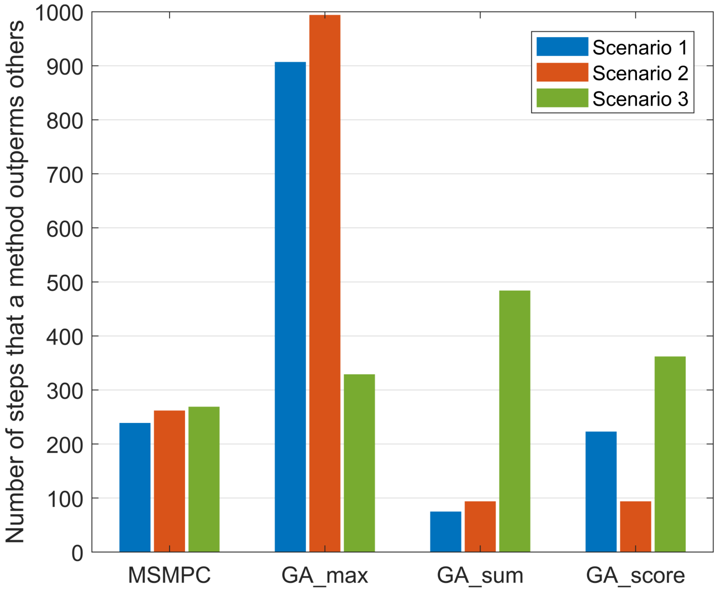

Fig. 4 Bar chart that shows the number of steps that a given method outperforms others for three scenarios.

of the occurrence of any high-impact event (Scenarios 1 or 2). Therefore, it is only recommended for RTC-WRM applications unless the decision maker ensures that high-impact events are unlikely to happen in the future.

GA_score is a weight-sum method that is developed based on the minisum criterion. Compared to GA_sum, its performance increases in Scenario 1 but decreases in Scenario 3. It is recommended to replace GA_sum if decisions need to be made by taking high-impact events into account.

It should be noted that GA_max, GA_sum, and GA_score are based on the same optimization framework of GA-MSMPC but they use different ways to select the solution from the Pareto optima set. GA_max shows a better performance than MSMPC with respect to all three scenarios while GA_sum and GA_score only show a better performance than MSMPC with respect to Scenario 3. Therefore, GA-MSMPC with the minimax criterion can replace MSMPC in order to makie better decisions in the face of different scenarios. However, it is difficult to conclude which method between GA_max, GA_sum, and GA_score is the absolute best because we usually do not know which scenario may happen in the future.

5.2 Implication for RTC Applications

Another concern of importance for RTC applications is the computational complexity. The current popular algorithm to solve a single-objective optimization problem, the interior-point algorithm, is in a cubic order of the forecast horizon and the number of control variables (Wang and Boyd, 2010). When taking a longer forecast horizon into account, the computation time greatly increases for the interior-point algorithm as used in MSMPC (Fig. 5). On the other hand, the computational complexity of NSGA-II only depends on the number

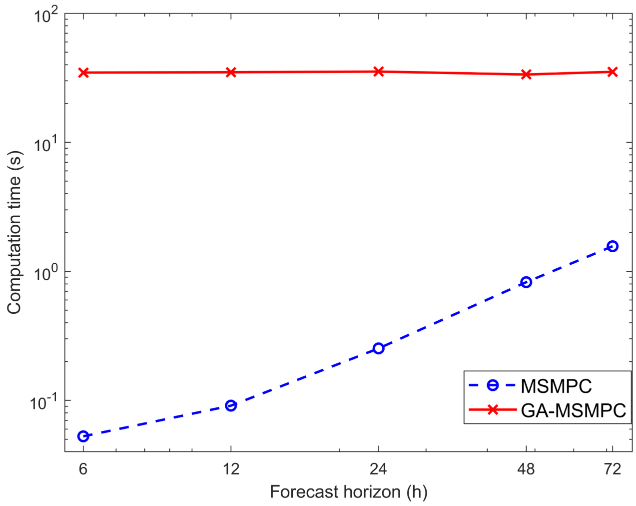

Fig. 5 Log-log plot of the computation time versus the forecast horizon.

of objectives and the second order of population size (Deb et al., 2002). When applying NSGA-II to solve problems of a long forecast horizon, its computation time varies insignificantly as the objectives and the population size are fixed (Fig. 5). Our study used six hours as the forecast horizon to test the performance of both real-time control approaches. Both MSMPC and GA-MSMPC were able to solve the problem within one minute. However, even if the computation time increased, MSMPC still ran much faster than GA-MSMPC for events with 72-hour forecasts, which were usually the maximum length for most weather nowcasting models. Therefore, MSMPC can suit an RTC problem better than GA-MSMPC at this stage in terms of computational efficiency. However, GA-MSMPC has greater potential when forecasting models are able to better predict more long-term weather.

5.3 Limitation of This Study

Our study is the first attempt to solve multi-scenario WRM problems by coupling MOEA and MPC. We adopted the NSGA-II algorithm due to its computational speed, which is required for RTC problems. Besides, we used twenty ensemble forecasts to represent plausible future states. With the development of weather radar, rainfall and runoff forecasting models are becoming more precise in many catchments. A better forecasting model will lead to a better controller. However, the approaches proposed in our study are generic and they can be combined with any forecasting model of a specific catchment.

Without additional preference information, no single solution can be determined for an optimization problem with conflicting objectives or scenarios. Improving one objective commonly deteriorates one or more remaining objectives. Therefore, although we are able to find a set of Pareto optimal solutions, it is still an open question about how to choose one solution from the solution set. For instance, no method in our study has the best performance in all scenarios.

6 Conclusions and Future Research

This study proposed a multi-scenario Model Predictive Control approach based on a genetic algorithm to cope with hydrological uncertainty in a real-time water level regulation problem. A case study of the North Sea Canal was conducted. Compared to the classic MSMPC approach based on the weighted sum approach, GA-MSMPC with the minimax criterion can better meet the management objectives although it has a heavier computational burden. In practice, GA-MSMPC benefits a bunch of problems that involve ensemble hydrological forecasts and multiple management objectives. With the rapid development of the MOEAs, GA-MSMPC has great potential to be applied to more RTC problems, which will be the direction of our future research.

Acknowledgments

Financial support from 'Spanish MINECO (project reference DPI2017-86918-R)' and 'Natural Science Research Projects for Universities of Jiangsu Province (17KJB170016)' is gratefully acknowledged.

Compliance with Ethical Standards

Conflict of Interest The authors declare that they have no conflict of interest.

References

Beh EHY, Maier HR, Dandy GC (2015) Adaptive, multiobjective optimal sequencing approach for urban water supply augmentation under deep uncertainty. Water Resources Research 51(3):1529–1551, DOI 10.1002/2014WR016254

Camacho E, Bordons C (1999) Model predictive control. Spinger, Sevilla, Spain

Coello Coello C, Lechuga M (2002) MOPSO: a proposal for multiple objective particle swarm optimization. In: Proceedings of the 2002 Congress on Evolutionary Computation. CEC'02 (Cat. No.02TH8600), IEEE, vol 2, pp 1051–1056, DOI 10.1109/CEC.2002.1004388

Deb K, Pratap A, Agarwal S, Meyarivan T (2002) A fast and elitist multiobjective genetic algorithm: NSGA-II. IEEE Transactions on Evolutionary Computation 6(2):182–197, DOI 10.1109/4235.996017

Deltares (2013) SOBEK-User manual

Ficchì A, Raso L, Dorchies D, Pianosi F, Malaterre PO, Van Overloop PJ, Jay-Allemand M (2016) Optimal Operation of the Multireservoir System in the Seine River Basin Using Deterministic and Ensemble Forecasts. Journal of Water Resources Planning and Management 142(1):05015005, DOI 10.1061/(ASCE)WR.1943-5452.0000571

Galelli S, Goedbloed A, Schwanenberg D, van Overloop PJ (2014) Optimal Real-Time Operation of Multipurpose Urban Reservoirs: Case Study in Singapore. Journal of Water Resources Planning and Management 140(4):511–523, DOI 10.1061/(ASCE)WR.1943-5452.0000342

Giuliani M, Castelletti A, Pianosi F, Mason E, Reed PM (2016) 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, DOI 10.1061/(ASCE)WR.1943-5452.0000570
Grosso J, Ocampo-Martínez C, Puig V, Joseph B (2014) Chance-constrained model predictive control for drinking water networks. Journal of Process Control 24(5):504–516, DOI 10.1016/j.jprocont.2014.01.010
Joseph-Duran B, Ocampo-Martinez C, Cembrano G (2014) Hybrid modeling and receding horizon control of sewer networks. Water Resources Research 50(11):8497–8514, DOI 10.1002/2013WR015119
Katz RW, Parlange MB, Naveau P (2002) Statistics of extremes in hydrology. Advances in Water Resources 25(8-12):1287–1304, DOI 10.1016/S0309-1708(02)00056-8
Kim M, Hiroyasu T, Miki M, Watanabe S (2004) SPEA2+: Improving the Performance of the Strength Pareto Evolutionary Algorithm 2. pp 742–751, DOI 10.1007/978-3-540-30217-9_75
Loucks DP, van Beek E, Stedinger JR, Dijkman JP, Villars MT (2005) Water Resources Systems Planning and Management and Applications: An Introduction to Methods, Models and Applications, vol 51. DOI 92-3-103998-9
Maciejowski J (2002) Predictive control: with constraints, 1st edn. Prentice Hall
Maestre JM, Negenborn RR (2014) Distributed Model Predictive Control Made Easy, Intelligent Systems, Control and Automation: Science and Engineering, vol 69, 1st edn. Springer, Dordrecht, Dordrecht, DOI 10.1007/978-94-007-7006-5
Maestre JM, Raso L, van Overloop PJ, De Schutter B (2013) Distributed tree-based model predictive control on a drainage water system. Journal of Hydroinformatics 15(2):335, DOI 10.2166/hydro.2012.125
Maier H, Kapelan Z, Kasprzyk J, Kollat J, Matott L, Cunha M, Dandy G, Gibbs M, Keedwell E, Marchi A, Ostfeld A, Savic D, Solomatine D, Vrugt J, Zecchin A, Minsker B, Barbour E, Kuczera G, Pasha F, Castelletti A, Giuliani M, Reed P (2014) Evolutionary algorithms and other metaheuristics in water resources: Current status, research challenges and future directions. Environmental Modelling & Software 62:271–299, DOI 10.1016/j.envsoft.2014.09.013
Maier H, Guillaume J, van Delden H, Riddell G, Haasnoot M, Kwakkel J (2016) An uncertain future, deep uncertainty, scenarios, robustness and adaptation: How do they fit together? Environmental Modelling & Software 81(April):154–164, DOI 10.1016/j.envsoft.2016.03.014
Malaterre PO, Rogers DC, Schuurmans J (1998) Classification of Canal Control Algorithms Controlled variables. Journal of Irrigation and Drainage Engineering 124(1):1–18, DOI 10.1061/(ASCE)0733-9437(1998)124:1(3)
Mathworks (2018) MATLAB Tutorials
Matrosov ES, Huskova I, Kasprzyk JR, Harou JJ, Reed PM (2015) Many-objective optimization and visual analytics reveal key planning trade-offs for London's water supply. Journal of Hydrology 531(2005):1040–1053, DOI http://dx.doi.org/10.1016/j.jhydrol.2015.11.003
Negenborn RR, van Overloop PJ, Keviczky T, De Schutter B (2009) Distributed model predictive control for irrigation canals. In: Networks and Heterogeneous Media, vol 4, pp 359–380, DOI 10.3934/nhm.2009.4.359
van Overloop PJ (2006a) Drainage control in water management of polders in the Netherlands. In: Irrigation and Drainage Systems, vol 20, pp 99–109, DOI 10.1007/s10795-006-5424-0
van Overloop PJ (2006b) Model predictive control on open water systems. PhD thesis, Delft University of Technology

van Overloop PJ, Weijs S, Dijkstra S (2008) Multiple Model Predictive Control on a drainage canal system. Control Engineering Practice 16(5):531–540, DOI 10.1016/j.conengprac.2007.06.002

Raso L, Malaterre PO (2016) Combining Short-Term and Long-Term Reservoir Operation Using Infinite Horizon Model Predictive Control. Journal of Irrigation and Drainage Engineering p B4016002, DOI 10.1061/(ASCE)IR.1943-4774.0001063

Raso L, Schwanenberg D, van de Giesen N, van Overloop PJ (2014) Short-term optimal operation of water systems using ensemble forecasts. Advances in Water Resources 71:200–208, DOI 10.1016/j.advwatres.2014.06.009

Reed P, Hadka D, Herman J, Kasprzyk J, Kollat J (2013) Evolutionary multiobjective optimization in water resources: The past, present, and future. Advances in Water Resources 51:438–456, DOI 10.1016/j.advwatres.2012.01.005

Schuurmans J, Hof A, Dijkstra S, Bosgra OH, Brouwer R (1999) Simple Water Level Controller for Irrigation and Drainage Canals. Journal of Irrigation and Drainage Engineering 125(4):189–195, DOI 10.1061/(ASCE)0733-9437(1999)125:4(189)

Stelling GS, Duinmeijer SPA (2003) A staggered conservative scheme for every Froude number in rapidly varied shallow water flows. International Journal for Numerical Methods in Fluids 43(12):1329–1354, DOI 10.1002/fld.537

Tian X (2015) Model Predictive Control for Operational Water Management: A Case Study of the Dutch Water System. PhD thesis, Delft University of Technology, Delft, the Netherlands

Tian X, van Overloop PJ, Negenborn RR, van de Giesen N (2014) Operational flood control of a low-lying delta system using large time step Model Predictive Control. Advances in Water Resources 75:1, DOI 10.1016/j.advwatres.2014.10.010

Tian X, Negenborn RR, van Overloop PJ, María Maestre J, Sadowska A, van de Giesen N (2017) Efficient Multi-scenario Model Predictive Control For Water Resources Management With Ensemble Streamflow Forecasts. Advances in Water Resources 109:58–68, DOI 10.1016/j.advwatres.2017.08.015

Trivedi A, Srinivasan D, Sanyal K, Ghosh A (2016) A Survey of Multiobjective Evolutionary Algorithms based on Decomposition. IEEE Transactions on Evolutionary Computation pp 1–1, DOI 10.1109/TEVC.2016.2608507

Vermuyten E, Meert P, Wolfs V, Willems P (2018) Combining Model Predictive Control with a Reduced Genetic Algorithm for Real-Time Flood Control. Journal of Water Resources Planning and Management 144(2):04017083, DOI 10.1061/(ASCE)WR.1943-5452.0000859

Vogel RM, Lall U, Cai X, Rajagopalan B, Weiskel PK, Hooper RP, Matalas NC (2015) Hydrology: The interdisciplinary science of water. Water Resources Research 51(6):4409–4430, DOI 10.1002/2015WR017049

Walsh CL, Blenkinsop S, Fowler HJ, Burton A, Dawson RJ, Glenis V, Manning LJ, Jahanshahi G, Kilsby CG (2016) Adaptation of water resource systems to an uncertain future. Hydrology and Earth System Sciences 20(5):1869–1884, DOI 10.5194/hess-20-1869-2016

Wang Y, Boyd S (2010) Fast Model Predictive Control Using Online Optimization. In: IEEE Transactions on Control Systems Technology, vol 18, pp 267–278, DOI 10.1109/TCST.2009.2017934

Xu M (2013) Real-time Control of Combined Water Quantity & Quality in Open Channels. PhD thesis, Delft University of Technology, Delft, the Netherlands