Case Study

Real-Time River Flood Control under Historical and Future Climatic Conditions: Flanders Case Study

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Abstract: Model predictive control (MPC) has shown to be an efficient technique for real-time flood control. The evaluation of the control performance is, however, typically restricted to a limited set of flood events. In this paper, the control performance is evaluated for a long-term time series of 116 years of meteorological data as well as after climate scenarios. Such an evaluation became feasible thanks to the use of a computationally efficient MPC approach based on a fast conceptual river model and an adapted genetic algorithm. The uncertainties related to the river model and the rainfall forecasts were accounted for. The influence of these uncertainties on the MPC control performance was, however, found to be limited after applying data assimilation. Comparing the proposed MPC approach to a standard programmable logic control (PLC)-based regulation shows that – despite the presence of uncertainties – MPC outperforms the PLC-based approach because it strongly reduces the incurred damage cost, the flood risk, and the frequency of flooding. This is still the case after considering the climate scenarios. **DOI: 10.1061/(ASCE)WR.1943-5452.0001144.**

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Introduction

During recent decades, the number of river floods has steadily increased in many parts of the world (EM-DAT 2005; MEA 2005; Brouwers et al. 2015). Two examples of ongoing trends associated with this increase are the increasing trend of extreme rainfall events due to climate change (Lehner et al. 2006; Willems et al. 2012; IPCC 2014; Vansteenkiste et al. 2014) and rising urbanization (Huang et al. 2008; Hawley and Bledsoe 2011; Poelmans et al. 2011). Model predictive control (MPC) strongly reduces the impact of these economically costly natural disasters in comparison with classic programmable logic controller (PLC)-based control strategies (Barjas-Blanco et al. 2010; Breckpot et al. 2013; Chiang and Willems 2015). Several successful applications of improved reservoir operation by MPC can be found in the literature (Galelli et al. 2014; Schwanenberg et al. 2014; Tian et al. 2015; Ficchi et al. 2016).

MPC was first used in the chemical process industry (Wendt et al. 2002; Nagy 2009), but in the meantime this technique has been widely used for many other control applications (Qin and Badgwell 2003). For flood control applications, a nonlinear river model is recommended to simulate the nonlinear river system dynamics that are excited during flooding. The resulting optimization problem is a nonlinear and nonconvex programming problem, which is difficult to solve. Nonlinear MPC is one of the successfully tested solutions to this problem (Barjas-Blanco et al. 2010; Schwanenberg et al. 2010; Breckpot et al. 2013) but has important obstacles related to computational efficiency and global optimality. Therefore, Vermuyten et al. (2018a) presented a combination of MPC and a reduced genetic algorithm (RGA) as a successful and fast alternative for classic MPC controllers, utilizing fast conceptual river models. This heuristic optimization method can solve nonlinear, nonconvex optimization problems and has been successfully applied to the Demer basin in Belgium, but only after assuming ideal circumstances of no uncertainties in the river model and the rainfall forecasts. For the single flood events in that case, damage cost reductions between 2% and 31% were obtained with the combined RGA-MPC technique in comparison to the current PLC-based regulation.

The optimization process of RGA-MPC depends on hydrologic and hydraulic models and rainfall forecasts in order to anticipate future rainfall events. The performance of such a model-based approach inevitably depends on the magnitude of errors and uncertainties (Walker et al. 2003; Brandimarte and Baldassarre 2012). Consequently, these uncertainties must be considered when comparing the proactive MPC controller with the reactive PLC-based regulation. Therefore, this study introduces both a hydrodynamic model and rainfall uncertainty to the RGA-MPC optimization process.

The feedback mechanism of MPC, based on the receding horizon strategy, systematically eliminates model deviations, resulting in some inherent robustness toward uncertainties (De Nicolao et al. 1996; Magni and Sepulchre 1997; Mayne et al. 2000). For large

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uncertainties, however, the impact of this inherent robustness is limited and the optimization algorithm needs to be extended with efficient model-updating algorithms and uncertainty propagation techniques (Sarma et al. 2006). Such data assimilation (DA) methods update the river model and flood forecasts based on observations (Hutton et al. 2011, 2014a, b; Liu et al. 2012). The flexible DA approach presented in Vermuyten et al. (2018b) is used in this study to account for uncertainties and systematically eliminate the deviations between predictions and observations.

The purpose of this study is to statistically investigate the impact of model and rainfall uncertainty on MPC performance, compare the flood control management of the PLC-based regulation and the MPC regulation while accounting for uncertainties, and assess the impact of future climatic conditions on the efficiency of both flood control management strategies. For this, a long-term series of 116 years of meteorological data are considered for the analyses, rather than analyzing a limited set of single flood events. This approach is possible thanks to the high computational efficiency of the RGA-MPC technique.

Study Area

The Demer basin in Belgium is a densely populated area of 2,334 km^2, mostly consisting of loam and sand. The Demer river, which is the main stream of the basin, and its most important tributaries (Herk, Velpe, and Gete) are highly sensitive to rainfall. The average downstream discharge of the Demer river in the summer (August) is 6 m^3/s, and 34 m^3/s in the winter (December). The basin's average annual rainfall is approximately 800 mm.

The Demer basin is a very flood-prone area with a long history of floods. The Flemish government has installed several hydraulic structures and flood retention basins to reduce the flood risk in this area. These hydraulic structures are currently operated individually by means of reactive PLCs. Typically, these PLCs only consider the current upstream and downstream water level of the hydraulic structures to determine the gate control actions based on if-then-else rules. This local, instantaneous, and static control strategy is expected to result in nonoptimal control actions. Consequently, severe floods still occurred during the storms of September 1998 and February 2002, amongst others.

This paper considers the subbasin of the river Herk as the study area. This subbasin covers the rivers Kleine Herk in the north and Grote Herk in the south. An inline retention basin with a storage capacity of 700,000 m^3 is installed to protect the city of Stevoort (Fig. 1). The water flow in this network is regulated by three hydraulic structures. The Flemish Environment Agency (VMM) has implemented a full hydrodynamic river model of this subbasin in the InfoWorks RS software version 14.0, based on detailed cross section data. This model includes the main floodplains, retention basin, and hydraulic structures.

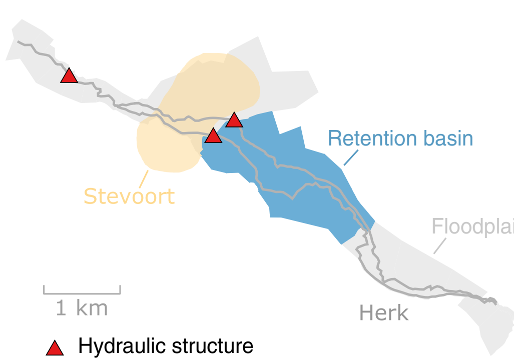

Fig. 1. River network of the Herk case study, together with the retention basin, the hydraulic structures, and the city of Stevoort.

Materials and Methods

Conceptual Modelling

A full hydrodynamic river model, implemented in the InfoWorks RS software, is available for the study area, but this type of model is too computationally slow for optimization applications. Therefore, this study makes use of conceptual models created semiautomatically by means of the conceptual model developer (CMD) tool from Wolfs et al. (2015). In this modelling approach, the entire network is divided into distinct units to simplify the network topology according to the storage cell concept. This results in a surrogate model or emulator that is less detailed than the full hydrodynamic river model, but computationally much more efficient. Simulation results with the full hydrodynamic model are used to calibrate the conceptual model. The number of locations with water level and discharge observations is too limited to allow direct calibration of the conceptual model for these data (Meirlaen et al. 2001; Vanrolleghem et al. 2005). Successful applications of conceptual models include river flood analysis, integrated catchment modelling, and recently, real-time flood control (Wolfs et al. 2012; De Vleeschauwer et al. 2014; Wolfs et al. 2016; Meert et al. 2016; Vermuyten et al. 2018a).

The conceptual model schematizes the river network by reservoirs interconnected by hydraulic structures. The flows over these structures are used to calculate the volume in each reservoir based on a mass balance equation. Hypsometric curves transform the reservoir volumes to water levels at one or more locations along the river reach, represented by each reservoir. Based on these water levels, the flows over the hydraulic structures and the different control objectives are calculated. The inputs to the conceptual model are rainfall-runoff discharges. These can originate from measured or synthetic hydrographs or hydrological models. This study makes use of the same rainfall-runoff model as considered in the full hydrodynamic InfoWorks RS model, which is the probability-distributed model (PDM) (Moore 1985, 2007).

Model Predictive Control and Reduced Genetic Algorithm

This study makes use of the RGA-MPC approach developed by Vermuyten et al. (2018a) for real-time flood control. The RGA-MPC technique applies MPC to the fast conceptual river model and considers an RGA for optimizing the future gate positions. MPC uses the predictions of the future system states generated by the conceptual river model in order to determine the regulation that minimizes the flood damage along the river network. In this way, the interaction between the different hydraulic structures is taken into account and the controller can anticipate future rainfall and flow conditions. Consequently, this proactive MPC controller results in an improved control strategy in comparison to the local reactive PLC-based control strategy, as shown by Vermuyten et al. (2018a) under idealized conditions by assuming perfect rainfall and model predictions.

At each control time step of MPC, a new optimization with RGA is performed. First the initial conditions of the prediction model are updated in order to represent the actual system states. Next, gate level (GL) scenarios representing possible future control strategies are generated. The RGA heuristic optimization method strongly reduces the number of possible solutions by considering

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only the gate operation positions at a subset of the future time moments as optimization variables. New GL scenarios can be generated randomly or by mutating the best control strategy so far. Each newly generated control strategy is analyzed by applying it to the conceptual river model and comparing the results with those of the best regulation so far. The best control strategy is selected based on the control objectives and used during the next iteration until the stopping criteria are met. The RGA converges faster towards a near-optimal solution than a standard genetic algorithm. For more details about the RGA-MPC technique, the interested reader is referred to Vermuyten et al. (2018a).

Hydrodynamic Model Uncertainty

Hydrodynamic river-model uncertainties result in deviations between the flood predictions used in the optimization process and the actual river observations. The main cause of these deviations is the strong seasonal variation in riverbed vegetation, which influences the flow regime along the river network. The influence of the vegetation is limited in winter conditions, while the increased vegetation in summer results in higher riverbed roughness and, accordingly, in higher water levels (De Doncker 2010). The InfoWorks RS model of the Demer basin uses Manning's roughness coefficient to model riverbed roughness. Two vegetation growth scenarios are considered in this study: an average vegetation growth scenario, and a summer vegetation growth scenario with increased riverbed roughness. For both scenarios, a conceptual river model is calibrated based on the results of the InfoWorks RS model with adjusted settings for the Manning coefficients. The differences in model simulation results between these two vegetation growth scenarios are assumed to be indicative of the hydrodynamic river model uncertainty. More details about this experimental setup and river model uncertainty quantification can be found in Vermuyten and Willems (2018).

Rainfall Uncertainty

MPC is known for its proactive control strategy, which means it can anticipate a future flood event. However, because of rainfall uncertainties, the wrong anticipatory control actions may be taken. For example, if the rainfall forecast of an event is overestimated, a city might be put under water based on that rainfall forecast to reduce the flood damage peak later on in the event, whereas for the actual rainfall it may have been possible to avoid any flood damage.

The inputs of the prediction model used in the MPC controller are rainfall-runoff (RR) forecasts. The uncertainty in these RR inputs is defined as rainfall uncertainty and originates from rainfall forecasts (rainfall forecast uncertainty) and the hydrological model (hydrological model uncertainty). RR forecasts and corresponding RR observations are required to investigate the effect of rainfall uncertainty on the real-time control performance. RR forecasts are, however, not available for this study. Therefore, an RR forecast generator was developed.

The RR forecast generation starts from the observed RR series. These RR series represent the actual rainfall over the river catchment and originate from synthetic hydrographs or from a hydrological model after applying historical rainfall and evapotranspiration inputs. The purpose of the forecast generator is to create for each event a set of RR forecasts based on the observed historical RR series. To this end, random rainfall forecast errors are added to the observed RR series; they are sampled from a distribution of rainfall forecast errors and assessed based on historical forecast errors, as per the method explained by Timbe (2007) and Barjas-Blanco et al. (2010).

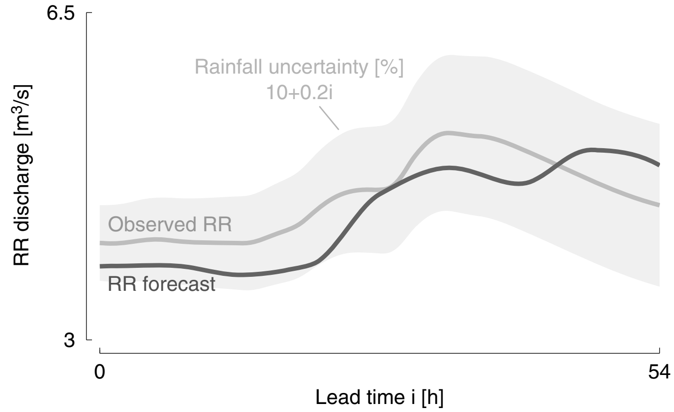

Fig. 2. Example of an RR forecast (black) generated from an observed RR series (dark grey), together with the error band (light grey).

Rainfall uncertainty increases with an increasing prediction horizon. For the same study region, Timbe (2007) quantified that the relative rainfall forecast error ranges from approximately -10% to approximately $+10\%$ at the time of forecast, increasing by 0.2% per hour over the prediction horizon. The same uncertainty estimates were applied by Barjas-Blanco et al. (2010). Based on these uncertainty estimates, the uncertain RR forecasts are generated as follows:

- At the time of forecast, a uniformly distributed random error percentage between -10% and $+10\%$ is created.
- Then, with fixed time intervals, a beta-distributed random error percentage between $-p$ and $+p$ is created. The variable p is defined as $10 + 0.2i$, with i the time in hours along the prediction horizon. The maximum of this beta distribution is set equal to the previous error percentage and the average set to the value corresponding to a fixed percentage between the previous error percentage and zero. By using beta distributions, the autocorrelation in the forecast error is taken into account (an overestimation at time t will probably also lead to an overestimation at time $t + \Delta t$).
- The generated random error percentages are then applied to the observed RR discharges at the corresponding time steps.
- A piecewise cubic hermite–interpolating polynomial is fitted through these error-perturbed discharges versus lead time, resulting in a stochastic RR forecast.

Fig. 2 shows an example of a stochastic RR forecast generated in this way. The forecast frequency, i.e., the frequency at which new forecasts become available, is 6 h in this study. The control horizon of the MPC controller is 48 h. Therefore, RR forecasts are generated with an interval of 6 h during the event and have a maximum lead time of 54 h.

Data Assimilation

Without a feedback mechanism, state predictions tend to drift away from the actual system states due to the presence of uncertainties. Data assimilation methods use river observations to update the initial states of the river model and improve its accuracy.

State estimators can update all system states based on a limited number of observations. This study uses the ensemble Kalman filter (EnKF) to update the initial states of the prediction model (Evensen 1994). Because the effect of such a state estimator reduces with increased lead time, a prediction error method was also applied to reduce the prediction errors due to uncertainties, as recommended by Madsen and Skotner (2005) and Vermuyten et al. (2018b).

The recently introduced flexible prediction error method (Flex PEM) by Vermuyten et al. (2018b) analyzes past model residuals and applies an appropriate error correction scheme to prior model predictions based on this analysis. The combined approach of the EnKF and Flex PEM reduces the loss in control performance due to hydrodynamic model uncertainty by about 75% (Vermuyten et al. 2018b).

Long-Term Analysis

In order to apply RGA-MPC to long-term series, a framework similar to that proposed in Vermuyten et al. (2018a, b) for single flood events is set up. In this case, a conceptual model is used to represent the physical river system (i.e., the simulation model) and the optimization procedure (i.e., the prediction model). When considering model uncertainty, the conceptual model representing average vegetation growth is used as the prediction model, while the conceptual model representing summer vegetation growth is used as the simulation model. Long-term RR series are considered as input for the conceptual models. Based on these input series, both PLC-based simulations and closed-loop MPC optimizations with a temporal frequency of 15 min and a control horizon of 48 h are performed. When considering rainfall uncertainty, uncertain RR forecasts generated with the methodology described above are applied to the prediction model, while the historical RR observations are applied to the simulation model. The number of considered GL scenarios per optimization step in MPC is limited to 200 as a stopping criterion. In order to further limit the computational time of the long-term MPC analyses, the controller first analyzes the damage cost for the PLC-based regulation over the next 48 h. If no flood damage is expected for this control strategy, the PLC-based regulation is applied and no optimization is performed. If the PLC-based regulation does not succeed in avoiding flood damage, the MPC controller optimizes the control strategy for the next 48 h and applies the resulting optimal control strategy to the simulation model. The flowchart in Fig. 3 summarizes the different steps taken by RGA-MPC to determine the future control strategy.

The results of both the PLC-based regulation and the MPC regulation are analyzed with respect to the cost of the incurred damages of the entire study area. The peak-over-threshold (POT) method is applied to the resulting long-term damage series, with a threshold equal to EUR 1,000. This means that each flood event with a damage peak larger than EUR 1,000 is selected and considered for the flood damage cost analysis. This analysis compares the damage costs of the flood events when applying the MPC regulation versus those of the PLC-based regulation. The damage cost over the complete long-term period is compared, as well as the number of flood damage events. Also, the return period of the different flood damage events is determined and plotted against the cost of incurred damages. Based on these results, the flood risk can be approximated by Deckers et al. (2010)

$$R \simeq \sum_{i=1}^{n-1} \left(\frac{1}{T_i} - \frac{1}{T_{i+1}} \right) * \left(\frac{D_i + D_{i+1}}{2} \right) + \frac{D_n}{T_n} \tag{1}$$

where R = total flood risk per year; n = number of flood events during the considered period; T_i = return period of flood event i; and D_i = damage cost of flood event i. The damage cost of a flood event consists of the economic damage cost, calculated by means of damage functions, and the cost for overtopping the retention basin dike. The latter is assessed based on the land-use socioeconomic data, by means of the LATIS tool (Deckers et al. 2010), which is the standard tool for assessing flood-related damage costs in Flanders.

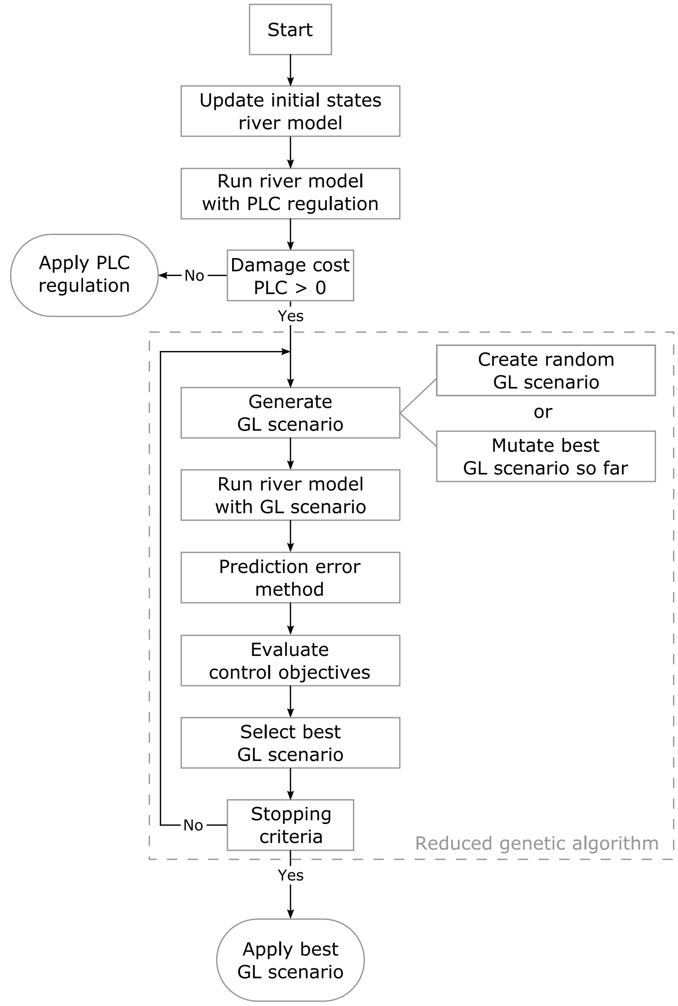

Fig. 3. Flowchart of the reduced genetic algorithm with data assimilation.

Historical Observations and Climate Scenarios

For the long-term analyses, an observed series of 116 years of hourly rainfall intensities, from January 1, 1900, until August 31, 2016, is applied. This series is simulated, together with daily potential evapotranspiration observations for the same period, as inputs to the PDM RR models of the Herk river. These lumped conceptual hydrological models deliver long-term RR input series for the conceptual river model. To assess the future impact of climate change on the Herk case study area, the observed rainfall and potential evapotranspiration series are modified.

For precipitation, an advanced change factor–based statistical downscaling method (Ntegeka et al. 2014) is applied, based on two steps. In the first step, rainfall events are added or removed depending on the change in the number of wet days. This change is defined as the ratio of the number of wet days for the future scenario period to the number of wet days for the historical period. For a ratio larger than 1, indicating an increasing number of wet days, dry days in the observed time series are converted into wet days. The rainfall amounts for these wet days are randomly sampled from the wet days in the observed time series. For a ratio smaller than 1, wet days in the historical time series are converted into dry days in a similar way. In the second step, the rainfall amounts are modified using exceedance probability–based changes. For all wet days, the corresponding exceedance probability is computed based on the

Table 1. Overview of the climate model ensemble

Modeling center or group	Model name	RCP 8.5	RCP 6.0	RCP 4.5	RCP 2.6	Model resolution (Lon x Lat)
Centre National de Recherches Meteorologiques/Centre Europeen de Recherche et Formation Avancees en Calcul Scientifique	CNRM-CM5	1	—	1	—	1.4° × 1.4°
College of Global Change and Earth System Science, Beijing Normal University	BNU-ESM	—	—	1	1	2.8° × 2.8°
Institut Pierre-Simon Laplace	IPSL-CM5A-LR	1	1	—	—	3.8° × 1.9°
	IPSL-CM5A-MR	1	1	—	1	2.5° × 1.3°
Japan Agency for Marine-Earth Science and Technology, Atmosphere and Ocean Research Institute (The University of Tokyo), and National Institute for Environmental Studies	MIROC-ESM-CHEM	1	1	1	1	2.8° × 2.8°
	MIROC-ESM	1	1	1	1	2.8° × 2.8°
Meteorological Research Institute	MRI-CGCM3	1	—	1	1	1.1° × 1.1°
Geophysical Fluid Dynamics Laboratory	GFDL-CM3	1	1	—	—	2.5° × 2.0°
	GFDL-ESM2G	1	1	1	1	2.5° × 2.0°
	GFDL-ESM2M	1	1	1	—	2.5° × 2.0°

total daily rainfall amount. Next, the observed daily rainfall amounts and corresponding subdaily variations are modified by the relative change in the daily rainfall amount with similar exceedance probability. Relative changes larger than 1 indicate the intensification of rainfall amounts, whereas changes smaller than 1 indicate drying. For evapotranspiration, the daily amounts are modified by the change in average daily evapotranspiration. This is the ratio of the average daily evapotranspiration amount for the scenario period to the amount for the historical period. All precipitation and evapotranspiration changes are defined and applied on a monthly time scale. More information on these changes can be found in Tabari et al. (2015) and Van Uytven and Willems (2018).

The modified time series are produced for a 29-membered CMIP5 global climate model ensemble, the composition for which is indicated in Table 1. The four most recent greenhouse gas scenarios of the Intergovernmental Panel on Climate Change (IPCC) are represented in this ensemble (van Vuuren et al. 2011; Taylor et al. 2012; IPCC 2014). Representative concentration pathway (RCP) 8.5 is the business as usual scenario for which the temperature rise at the end of the 21st century is not constrained and reaches above 4°C. The corresponding subensemble includes nine runs. On the other hand, RCP 2.6 is a strong mitigation scenario for which the average global temperature rise is limited to 1.7°C. The RCP 2.6 subensemble includes six runs. RCP 4.5 and RCP 6.0 are two intermediate mitigation scenarios. Both subensembles consist of seven runs. In this study, the historical period is defined as 1961–1990 and the scenario period as 2071–2100 (2085). Hence, the projected time series are representative of the end of the 21st century.

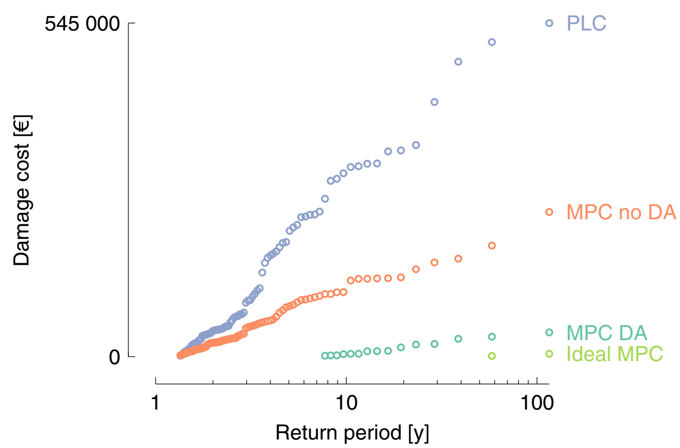

Fig. 4. Comparison of the incurred damage cost as a function of the return period when applying the PLC-based control strategy and the three considered MPC controllers, after historical rainfall observations.

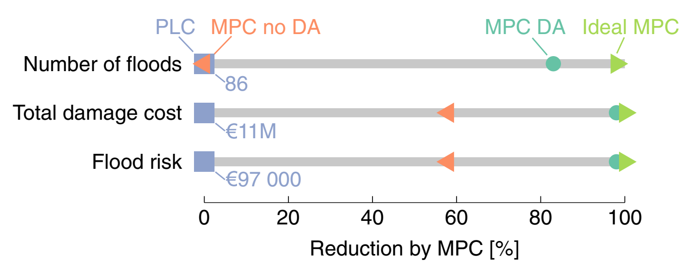

Fig. 5. Comparison of the reduction of the number of flood events, the total damage cost, and the annual flood risk by the three different MPC controllers toward the PLC-based regulation, after historical rainfall observations.

Results

Current Climatic Conditions

Figs. 4 and 5 summarize the damage cost analysis for the historical rainfall observations. This analysis only considers flood events with a damage cost higher than EUR 1,000. When applying the PLC-based regulation, flood events occur approximately once every 1.5 years. The maximum induced damage cost is equal to EUR 545,000. The 86 flood events that occur during the considered 116-year period result in a total damage cost of EUR 11 million. This corresponds to an annual flood risk of EUR 97,000.

When applying MPC under ideal circumstances (Ideal MPC), i.e., without considering model and rainfall uncertainty, only two flood events occur. The maximum induced damage cost is limited to EUR 5,000. This corresponds to a total damage cost and flood risk reduction close to 100% in comparison to the PLC-based approach, given that almost all flooding over the past 116 years is

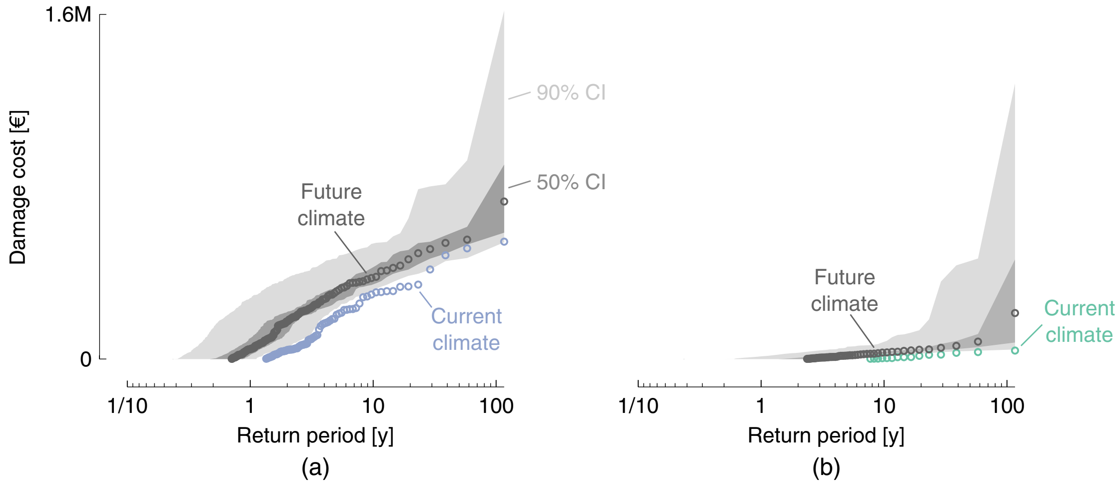

Fig. 6. Comparison of the incurred damage cost as a function of the return period for the current and future climatic conditions, after PLC- and MPC-based regulation: (a) PLC; and (b) MPC.

avoided. This improved control performance of MPC toward the PLC-based regulation can be explained by the anticipating capacity of MPC and its prediction window. MPC performs an overall optimization in which the operation of the various gates is coordinated rather than providing a local solution such as the PLC-based regulation. These regional, anticipating, and dynamic control actions, taking future conditions and system interactions into account, are the main advantage of model predictive controllers.

The presence of uncertainties can, however, lead the MPC controller to take the wrong anticipatory actions. In order to take these effects into account, model and rainfall uncertainties were introduced in the model setup as described in the methodology section. In this case, MPC without DA (MPC no DA) results in the same number of floods as the PLC-based regulation. The induced damage cost of each of these flood events is, however, strongly reduced. This results in a reduction of the total damage cost and the flood risk by 58%.

The introduction of a DA method (MPC DA) strongly reduces the impact of the considered uncertainties on the real-time control performance of MPC. As can be seen from Fig. 4, flood events occur approximately once every 8 years in this case. This corresponds to a reduction of the number of flood events by 83% towards the PLC-based regulation. For all 15 remaining flood events, the incurred damage cost is very low in comparison to the corresponding damage cost with the PLC-based regulation. The damage cost of a flood event with a return period of 116 years is limited to EUR 40,000, which is 93% less than with the PLC-based regulation. The total damage cost is reduced by 98%. Also, the annual flood risk is reduced by 98% and is now equal to EUR 1,900.

Based on the above results, it is concluded that MPC in combination with the applied DA method strongly outperforms the current PLC-based regulation for the current climatic conditions. Despite the presence of both model and rainfall uncertainties, the performance of MPC with DA is close to that of ideal MPC. MPC uses the available storage capacity more optimally, avoids unnecessary filling of the retention basin, and requires less storage to avoid flooding. In this way, more storage capacity remains available for possible future rainfall events and a better control performance is obtained than with the reactive PLC controllers. It is expected that the benefits of MPC toward the PLC-based approach will be even more clear when considering larger networks.

Future Climatic Conditions

Climate change scenarios are applied to the historical observations in order to further compare the flood control performance of the PLC- and MPC-based control strategies and to investigate whether they are climate proof and to what extent. The MPC results shown in this section are those obtained with the MPC controller with DA after introducing model and rainfall forecast uncertainty (MPC DA). Similar to the analysis of current climatic conditions, only flood events with a damage cost higher than EUR 1,000 are considered for the analysis.

Figs. 6 and 7 illustrate the impact of the different climate change scenarios for both the PLC- and MPC-based regulations. The results of the 29 considered climate change scenarios are represented by means of the median and the 50% and 90% confidence intervals (CI). As can be seen from Fig. 6, climate change will increase the frequency of flooding from less than once a year to more than once a year when applying the PLC-based regulation. With the MPC regulation, the flood frequency will increase from once every 8 years to once every 2 years, which is still less frequent than with the PLC-based regulation under the current climatic conditions.

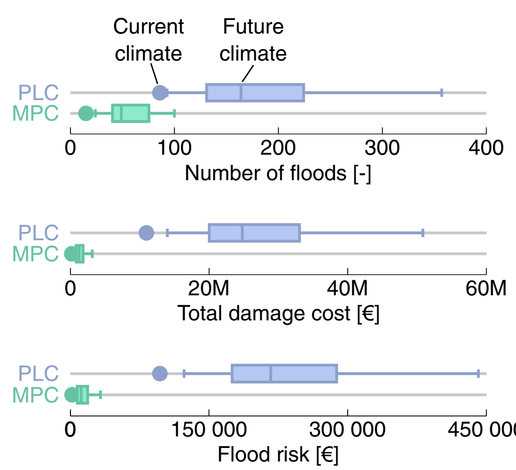

Fig. 7. Comparison of the number of flood events, the total damage cost, and the annual flood risk for the current and future climatic conditions, after PLC- and MPC-based regulation.

For both regulation strategies, the induced damage cost of each flood event will increase in the future. This increase is, however, more limited when applying MPC. Only the flood event with a return period of 116 years has an increase in damage cost of the same order of magnitude as with the PLC-based regulation. Also, the variation in the results due to climate change uncertainty is more limited with the MPC regulation, especially for return periods lower than 20 years. For higher return periods, the variation increases and is more similar to the PLC-based regulation. Nevertheless, the induced damage cost with MPC when considering climate change scenarios is consistently much lower than with the PLC-based regulation, even for the current climatic conditions. Only for flood events with a return period of 116 years are the variation in the results very high for both regulation strategies. However, flood events with a return period of 116 years when applying MPC have the same median damage cost as flood events with an approximate return period of 2.5 years when applying the PLC-based regulation.

Fig. 7 evaluates how climate change will affect the number of floods, the total flood damage cost, and the annual flood risk for both the PLC- and MPC-based regulations. The results of the 29 considered climate change scenarios are represented by means of boxplots. For both control strategies, the number of floods will increase due to climate change. However, this increase and also the variation in results is much larger with the PLC-based regulation. For more than 75% of the climate change scenarios, MPC still results in a lower number of floods than the PLC-based regulation does under the current climatic conditions. Moreover, the number of floods for the most severe climate change scenario when applying MPC is only slightly higher than the number of flood events for the least severe climate change scenario when applying the PLC-based regulation. Climate change will also increase the total flood damage cost and the annual flood risk for both control strategies. Again, both the increase and the variation are larger when applying the PLC-based regulation than with MPC. Moreover, the total damage cost and the annual flood risk when applying MPC are for all climate change scenarios much lower than when applying the PLC-based regulation for the current climatic conditions.

For events with a return period less than 2 years, MPC avoids flooding for almost all climate scenarios in comparison with the PLC-based regulation, as can be seen in Fig. 8. Also, for events with a higher return period, MPC reduces the damage cost by more than 79% for at least 75% of the climate scenarios. Only for the event with the highest return period of 116 years did damage cost reduction become worse and the variation increase. Nevertheless, MPC still obtains damage cost reductions of at least 21% for all climate scenarios. The damage cost reduction by MPC is even higher than 50% for 75% of the scenarios and can be as high as 93% for this extreme event.

For the future climatic conditions, the damage cost reduction by MPC decreases compared to the performance obtained for the current climatic conditions, see Fig. 8. This is, however, to be expected, because all climate change scenarios result in more extreme events. The more extreme an event, the more difficult it is to reduce the damage cost, as can be seen from Figs. 6 and 8. Moreover, the decrease in damage cost reduction is limited for events with a return period of 20 years or less. For events with a higher return period, MPC still outperforms the PLC-based regulation with respect to damage cost reduction.

MPC reduces the number of flood events by 83% in comparison with the PLC-based regulation for the current climatic conditions, see Fig. 9. Because climate change will result in more severe events, it has to be accepted that more flood events will occur, also after MPC, resulting in a lower reduction of the number of flood events. MPC, however, still achieves reductions between 57% and 81% toward the PLC-based regulation with respect to the number of floods. The reduction with respect to the total damage cost and the annual flood risk will also be lower for the future climatic conditions than for the current climatic conditions. The impact of climate scenarios on the reduction by MPC is, however, limited for both criteria because reductions of more than 90% are still obtained for the future climate scenarios.

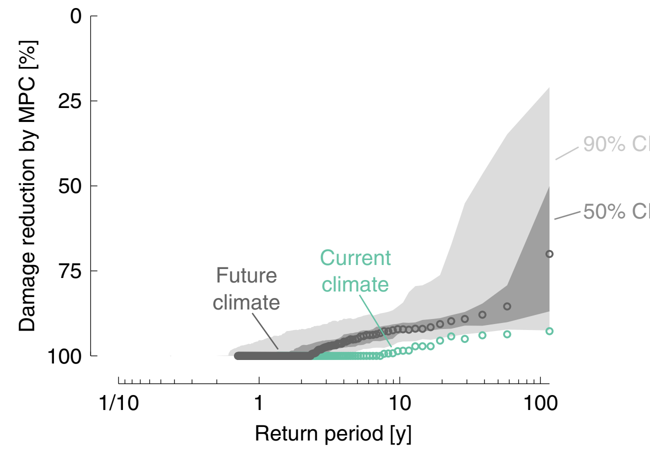

Fig. 8. Comparison of the damage cost reduction by MPC toward the PLC-based regulation as a function of the return period for the current and future climatic conditions.

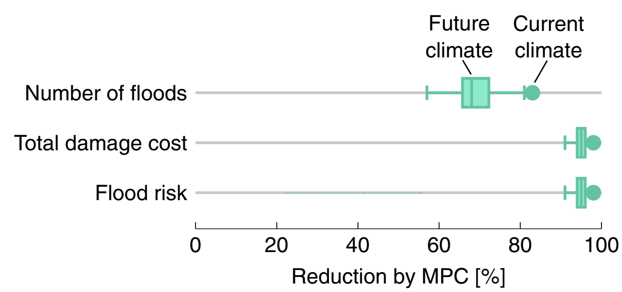

Fig. 9. Comparison of the reduction of the number of flood events, the total damage cost, and the annual flood risk by MPC toward the PLC-based regulation for the current and future climatic conditions.

In general, MPC strongly reduces the incurred damage cost and the flood risk in comparison with the PLC-based regulation. Moreover, flooding occurs less frequently, as can be seen from the reduced number of flood events and the corresponding return periods. Based on these findings, it is concluded that MPC outperforms the current PLC-based control strategy, not only for the current climate but also for climate scenarios. Consequently, the intelligent control system by means of MPC is more climate proof than the PLC-based control strategy.

Conclusions

Intelligent control systems are typically tested for single flood events because most classic MPC controllers are too computationally demanding to perform long-term analyses. Long-term analyses are, however, particularly useful to design new flood control infrastructure based on statistical analysis considering long time series of meteorological conditions, in order to perform risk analysis and to investigate the efficiency of the flood control system under changing climatic conditions, among others. Therefore, Vermuyten et al. (2018a) developed the RGA-MPC technique, which combines MPC with a computationally efficient RGA. This technique quickly converges toward near-optimal control strategies, allowing long-term optimizations to be conducted within a few hours. In this way, more comprehensive analyses can be performed, rather than considering only a limited set of individual flood events.

This study conducted the first long-term analyses for the current climatic conditions. The historical flooding in the Herk river was analyzed for the historical observations between 1900 and 2016. Under ideal circumstances, i.e., without considering model and rainfall uncertainties, MPC succeeds in avoiding almost all flooding when this 116-year time series is considered, corresponding to a damage cost reduction of EUR 11 million in comparison to the current PLC-based control strategy. This reduction is due to the anticipating capacity of MPC, which allows the controller to make use of the retention basin storage capacity at the most optimal point in time. In addition, MPC requires less flood storage to obtain this improved control performance, because it makes more optimal use of the available storage capacity. Model and rainfall forecast uncertainties can, however, have an important impact on the real-time control performance by MPC. The flexible DA method applied in this study strongly reduces this impact. Performances close to that of ideal MPC are obtained for the incurred damage cost, the flood risk, and the frequency of flooding.

In a second phase, climate scenarios by the end of the 21st century are considered. Because climate change results in more extreme events, the number of floods, the incurred damage cost, and the annual flood risk all increase. This increase is, however, more limited when applying MPC than with the PLC-based control strategy. For all climate scenarios, MPC strongly reduces the incurred damage cost, the flood risk, and the frequency of flooding in comparison with the PLC-based regulation. It is concluded that despite the presence of uncertainties, the intelligent control system by means of MPC is more climate proof and outperforms the current PLC-based control strategy.

It is advised to conduct follow-up studies in which the long-term analyses are also carried out for larger river basins. In this way, a more comprehensive analysis of the historical flood reduction and the impact of climate change can be obtained. Furthermore, the effect of rainfall forecast errors can be integrated into flood predictions by using ensemble predicting systems (EPS) (Van Steenbergen and Willems 2014). These EPS generate probabilistic forecasts by perturbing the initial conditions of the numerical weather prediction model. MPC, however, cannot explicitly deal with these uncertainties because it is a deterministic controller. Therefore, robust MPC methods have been developed to take these uncertainties into account. Examples are multiple MPC (van Overloop et al. 2008), adaptive multiple MPC (Delgoda et al. 2013), and tree-based MPC (Raso et al. 2014).

Data Availability Statement

Some or all data, models, or code generated or used during the study are available from the corresponding author by request.

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