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Model Predictive Control with SWMM

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Real time control (RTC) is particularly promising in large, flat and heterogeneous sewer systems with a high in-line storage volume. For the simulation of such systems with major backwater effects the use of dynamic routing models is indicated, but for model predictive control (MPC) such models are generally regarded as infeasible because they are computationally highly demanding and thus impractical to use for receding horizon applications.

This chapter focuses on the challenges and constraints of dynamic flow routing calculations for MPC. For the analysis a software framework was developed which enables MPC simulations using the dynamic sewer network model SWMM 5 (Rossman, 2008). The software provides various optimization algorithms and offers different time horizons to take into account the time span required to evaluate the optimization objectives (prediction horizon), the time span for which system input is known in advance (forecast horizon), and the time span for which control devices have to be optimized (control horizon). For the formulation of control objectives, parameters representing flow and water quality conditions can be used. In the generated MPC framework, modules for optimization and flow simulation are separate, leading to a text-based parameter optimization procedure.

14.1 Background

Increased legal requirements to minimize the negative impacts of urban wastewater systems on receiving water bodies has reusulted in water resources management enjoying technological progress in many fields. Dynamic modeling of sewer networks has become a standard part of daily work in a broad community. Equipment for monitoring runoff and water

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quality online is substantially improving at the same time. These developments are supported by enhancements in PCs such as greater storage capacity, increased processor speed and parallel processing which allow for the storage of mass data and the modeling of more complex systems with reasonable run times.

On the other hand, financial constraints require solutions to minimize costs. Former boundaries between disciplines are redrawn (e.g. optimization methods and automation concepts are becoming part of water resources management). This leads to increased consideration of the feasibility of using RTC measures in urban drainage systems. However, not all networks require RTC. Control potential is generally available in heterogeneous sewer systems with low slopes. When modeling such systems flow dynamics must be considered, which requires the use of hydrodynamic models based on the Saint-Venant equations in order to adequately simulate backwater effects.

14.2 Principles of Model Predictive Control

14.2.1 Control Strategy

Generally two RTC strategies can be distinguished: rule based control (RBC) and model predictive control (MPC). Both strategies have in common that they use a control time step in which the control settings of the actuators in the sewer system are determined repeatedly. In RBC systems control decisions are derived offline during the design phase. In order to find control rules for nearly all potential flow conditions, many simulation runs are necessary thus making this process labor intensive. Control decisions are saved in a database (usually in the form of if-then rules) and are accessed during operation without significant time delay.

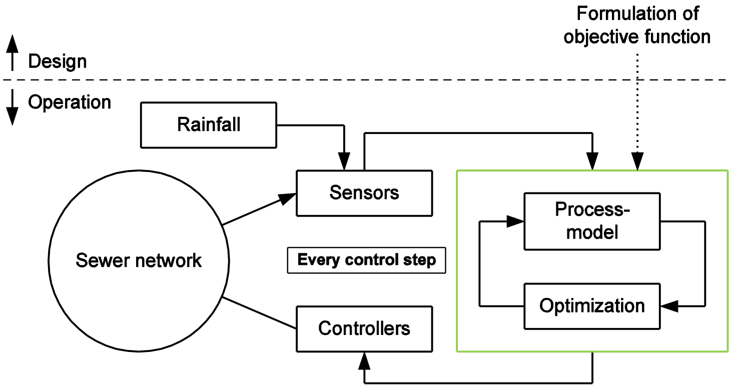


Figure 14.1 Principle of model predictive control (MPC).

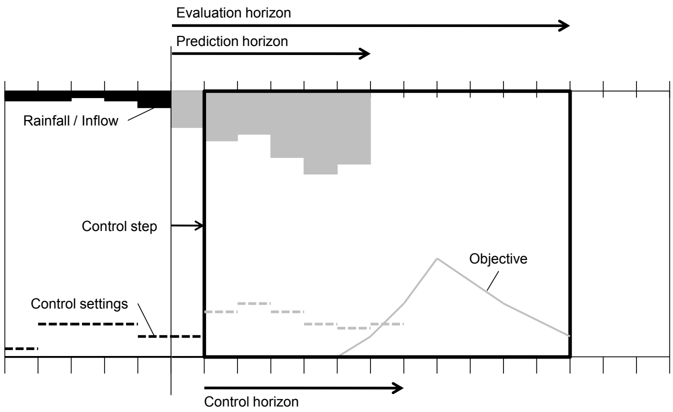
In MPC systems control decisions are calculated online during operation (Figure 14.1). During the design phase only the control objective has to be formulated. For the derivation of the control decision a software framework is required which contains an optimization module and a hydrodynamic process model to simulate the flow in the sewer network. The biggest challenge for MPC systems is the limited time available (i.e. the control step) to find optimal control settings for the immediate future under the given flow conditions.

MPC systems are characterized by three principles (Dittmar & Pfeiffer, 2004):

1. Explicit use of a process model to predict future states of the system;
2. Application of optimization algorithms to calculate the control settings; and
3. Implementation of the receding horizon.

14.2.2 Receding Horizon

MPC systems implement the principle of the receding horizon. It is a form of control in which the control action is obtained by solving a finite horizon optimal control problem repeatedly at each sampling instant (i.e. after every control step). Optimization yields an optimal sequence of future settings for all controlled actuators. Only the first control in this sequence is applied to the system though. The time horizon moves on by the length of the control step and after updating the current states of the system the optimization starts over again. The process is illustrated in Figure 14.2. Black objects and values display actual values which occurred or have been used in the past; grey objects and series values are calculated or predicted values in the future.



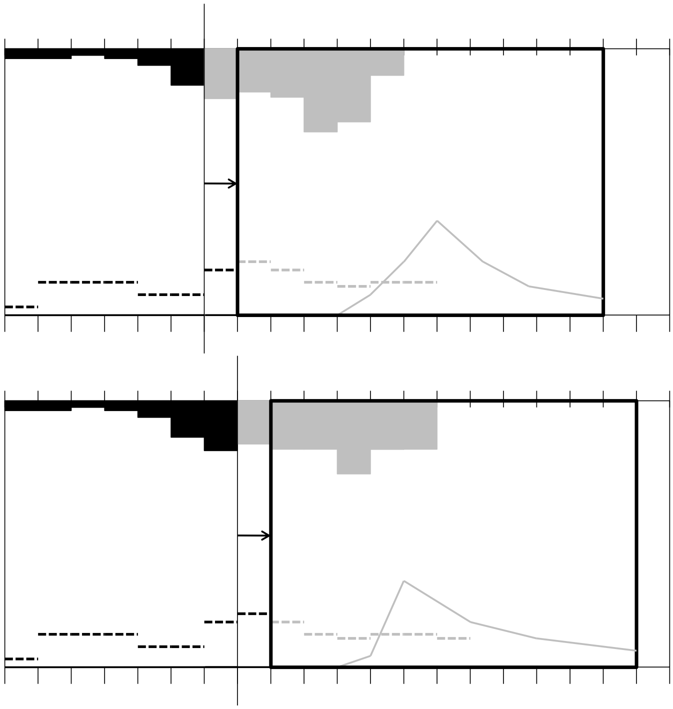


Figure 14.2 Principle of the receding horizon.

14.2.3 Standard Setup of MPC Software

A software framework for MPC has to include a process model to simulate flows in the sewer network and an optimization module to compute optimal control settings. Existing MPC software is usually based on derivative-based optimization algorithms (Figure 14.3) which require the calculation of numerical derivatives of the differential equations describing the flow process. Dynamic flow routing calculations are based on the Saint-Venant equations, which represent a system of hyperbolic differential equations. Optimal control of hyperbolic differential equations is still a research topic for which solutions are not yet readily available, so simplified process models are used. For example, in the case of linear transfer functions representing flow in the network the application of linear programming methods is possible.

With such systems optimal control settings can be identified quickly but the ability to model flow processes in dynamic systems with backwater effects has to be questioned.

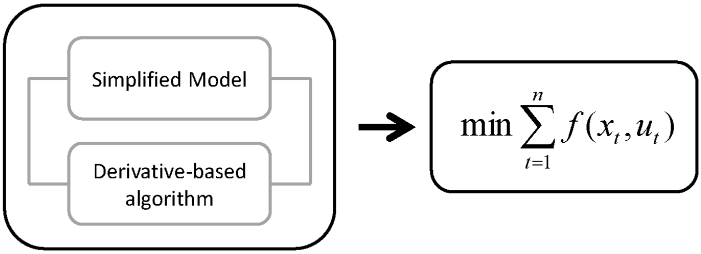


Figure 14.3 Standard setup of MPC software framework.

14.3 Setup of BlueM.MPC

In the scope of this research the software framework BlueM.MPC was developed (Figure 14.4). It implements the software BlueM.Opt (Muschalla et al., 2009) which incorporates various optimization algorithms. Currently the following algorithms are implemented:

- an evolutionary algorithm for solving real valued problems (Muschalla, 2006) including multi-threading capability;
- a hill-climbing algorithm for real valued problems (Hooke and Jeeves, 1961);
- a hybrid evolutionary algorithm using an evolutionary strategy for global optimization and using Hooke & Jeeves for local optimization (Kerber, and 2009) including multi-threading capability; and
- dynamically dimensioned search (DDS)—an n-dimensional continuous global optimization algorithm (Tolson & Shoemaker 2007).

A particular advantage of evolutionary algorithms is their capability to make use of parallelization features. The latest developments in computers have shown that standard PCs which include several CPU cores will soon be available, a feature which seems to be particularly promising for MPC applications.

With the focus on the application of dynamic flow routing models within MPC systems, SWMM 5 was integrated as a process model. SWMM 5 is well known to be reliable software by both practitioners and researchers and many datasets are already available.

The setup and workflow of BlueM.MPC is illustrated in Figure 14.4. For the application of the MPC module, information for the control time step and for the durations of the three horizons has to be provided. Once the control process has been started the same workflow applies to every control step: The optimization module generates SWMM 5 datasets which are simulated by either using an executable (SWMM5.exe) or a dynamic link library (SWMM5.dll). Simulation results are taken either from the resulting report file or by analyzing time series data. The results are evaluated by the optimization module which consequently generates a new dataset to continue with the optimization process. This approach strictly separates hydrodynamic simulation and optimization modules. Since it is not based on numerical derivations of the dynamic flow equations it is a derivative-free optimization method (black box optimization).

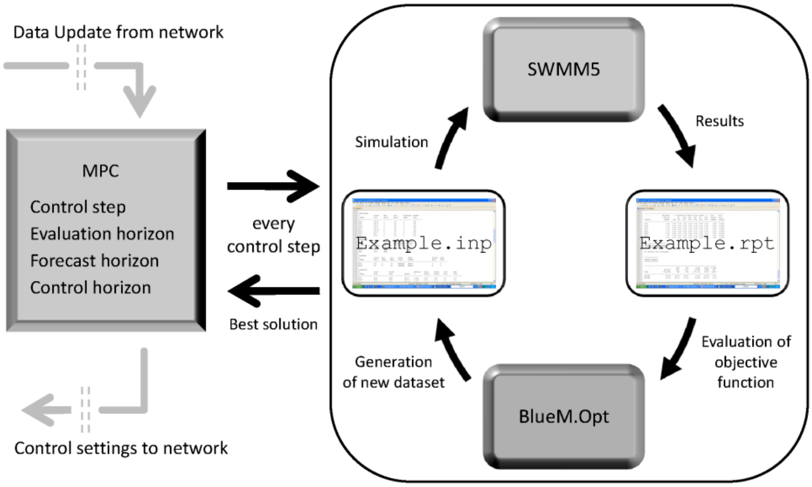


Figure 14.4 Setup and workflow of BlueM.MPC.

14.4 Case Study

In order to confirm the functionality of BlueM.MPC, calculations with a simple case study (Ifak, 2010) were performed (Figure 14.5). The system contains two subcatchments and two retention basins. Outflows from the upper retention basin can be controlled. Definition of the objective function includes minimization of the overflows from both storage basins. Additional penalty functions were applied for stored volumes to force the system to empty the basins whenever possible. For the results obtained, DDS algorithms were used. Calculations with other optimization algorithms yielded basically the same results, which leads to the conclusion that the strengths and weaknesses of the particular algorithms cannot be judged on the basis of such a simple case study.

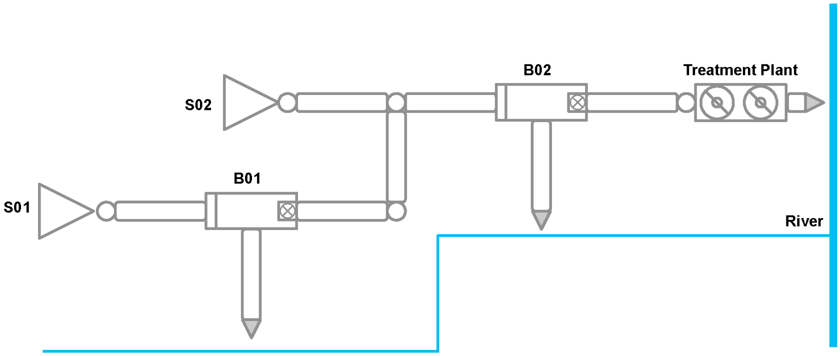


Figure 14.5 Case study network.

Even though the overall system contains only minor control potential the time series of the overflows (Figure 14.6) and water levels (Figure 14.7) from both basins show the functionality of the MPC system. In both figures the black lines show performances of the uncontrolled systems and grey lines performances of the MPC system.

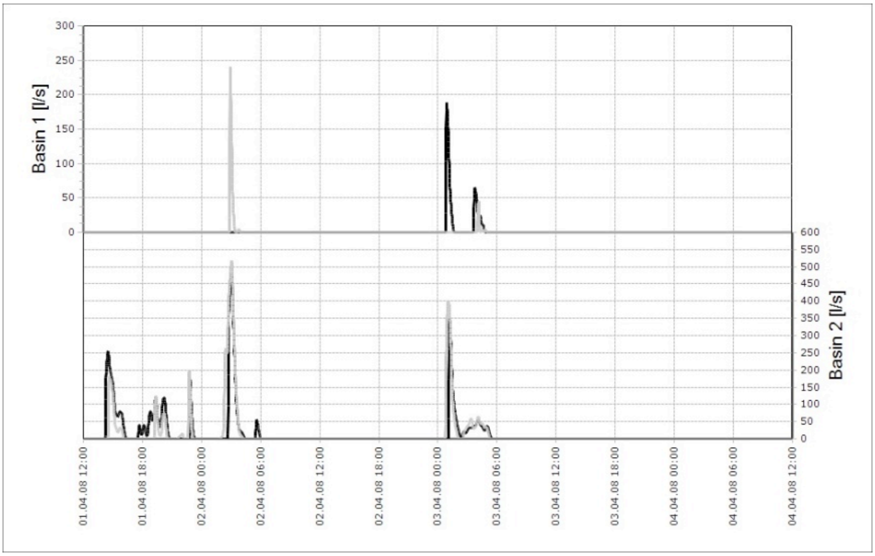


Figure 14.6 Overflows from storage basins (black series: no control, grey series: MPC).

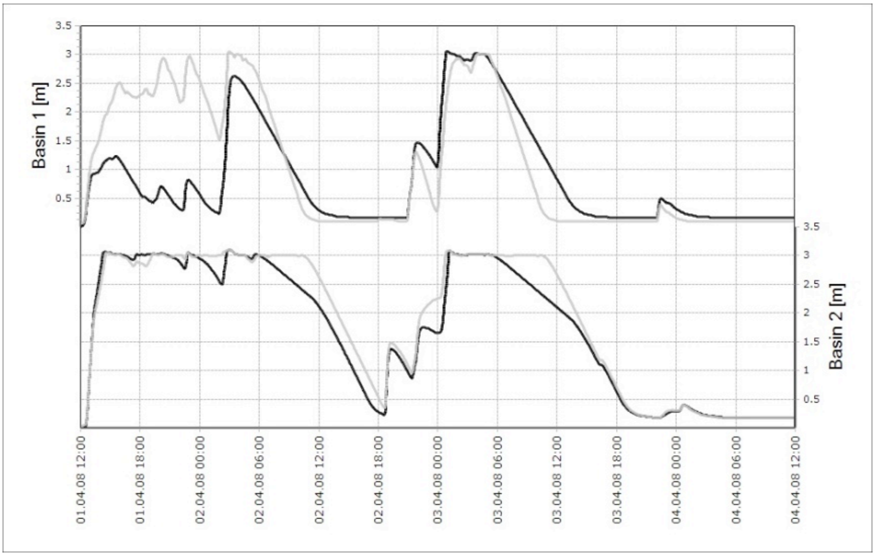


Figure 14.7 Water levels in storage basins (black series: no control, grey series: MPC).

In Figure 14.6, peaks in the second overflow event (at 00:00 2008 04 03) demonstrate the functionality of the MPC system. In Basin 1 (upper grey series) overflow is generated in the uncontrolled system while the MPC does not generate overflow. Water levels in Figure 14.7 confirm the behavior: levels of the MPC system in Basin 1 do not reach the level of the weir (3 m) at that point of time.

System functionality is also demonstrated by water levels at the beginning of the simulation period. The MPC system fills Basin 1 (Figure 14.7: upper grey series) in order to keep water levels in Basin 2 low which leads to smaller overflow volumes (Figure 14.6: lower grey series at 14:00 2008 04 01). Although higher water levels in Basin 1 lead to overflows at 03:00 2008 04 02 (Figure 14.6: upper grey series), overall the MPC system decreases overflow volumes for the total simulation period at approximately 3% which is close to the theoretical maximum decrease.

14.5 Challenges of Hydrodynamic MPC

The bottleneck for MPC calculations is created by the time restrictions from the control step since the optimal control decision for the following time interval has to be found within this available time period. Usually a 5 min control step is applied. This value results from hydraulic and from practical considerations. From the hydraulic point of view a longer time step would minimize the possibilities of influencing flows with respect to the defined objective function. For example, if the minimization of overflow volumes is defined as an objective function, control of storage volumes is a major factor. This task gets more difficult with increasing duration of the control. From a practical point of view a shorter time step would utilize the technical control devices such as pumps and sluice gates excessively.

Based on the iterative optimization approach of the developed MPC system, ultimately the questions have to be answered: How many simulation runs are possible within one control step and how many simulation runs are necessary within one control step?

The number of possible simulation runs within one control step depends on those factors which control the duration of a single simulation run:

- size of the sewer network (i.e. the number of nodes and links);
- the routing time step of the dynamic calculations; and
- the length of the evaluation horizon which determines the time span of a single simulation run.

The number of necessary simulation runs is depending on the following objectives:

- number of optimization variables, which is depending on the number of controllers in the network;
- the length of the control horizon and its discretization; and
- the optimization algorithm and its ability to find control settings of sufficient quality within the given time.

The example in Table 14.1 illustrates the problem range. It must be stressed that these numbers shall only give an idea of the order of magnitude of the size of the problem.

Table 14.1 Exemplary illustration of problem range.

Control step (5 min)	300 sec
Number of nodes in network	1 500
Evaluation horizon	3 h
Duration of one simulation run	10 sec
Number of possible simulation runs	30
Control horizon	1 h
Discretization of control horizon	5 min
Number of actuators in network	2
Number of optimization variables	24

The presented numbers are based on a selected control step of 5 min and a sewer network with 1 500 nodes (which might represent a small town of approximately 10 000 inhabitants). For the evaluation horizon 3 h was chosen (this time span is required to evaluate the objective function within a single simulation run). A fast computer should be able to compute such a dynamic model within 10 s. Ignoring delays for reading and writing the text files this leads to 30 possible simulations within the control step. Furthermore it is assumed that the network possesses two actuators for which settings have to be determined for a control horizon of 1 h in 5 min increments. This determines 24 optimization variables in the optimization problem.

Clearly, 30 simulation runs are not enough to find an optimal parameter set for 24 optimization variables with the iterative procedure provided by BlueM.MPC. Potential solutions to the problem are multi-threading and parallelization features. The evolutionary algorithm which is integrated in BlueM.MPC supports multi-threading making the use of multiple processors on one PC possible. Furthermore, for the hybrid algorithm software for parallelization was implemented, making the use of multiple computers within a network possible. These applications enable the multiplication of the number of possible simulation runs easily. Based on this, MPC of small networks seems to be feasible.

Considering that the control potential of a sewer network depends on the size of the network to a certain degree (i.e. small networks are less likely to have considerable control potential), prospects to apply a software framework like BlueM.MPC to large networks with a detailed model representation are small.

14.6 Conclusions

With BlueM.MPC a software framework was developed which enables the simulation of MPC systems with dynamic models. SWMM 5 is used as hydrodynamic process model to compute sewer flows, leading to a black box optimization approach to calculate optimal control settings. The software is flexible in regard to the optimization algorithms so that several different methods can be applied.

It was shown that dynamic models are generally applicable for MPC. To date problems with numerical stability have not been observed. Application of this modeling approach to small networks seems to be possible with currently available processors which use multi-threading or parallelization. The ability to control large networks is problematical, but might be achieved by the following:

- aggregating detailed models in order to shorten simulation runs (this does require the set up of a new model which has to be re-calibrated); and
- cutting branches which are not influenced by control actions.

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