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Control of Flood Defense Reservoirs System Under Uncertain Inflows: NYSA Reservoirs System Case Study

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Abstract

Floods and water use have been linked together since ancient times. Rivers provide water and keep the society alive, but they also cause danger: they damage properties and even take lives. During the last few decades we can observe an unusual frequency of flood events. High flood losses are typical either for developed or developing countries. Examples of enormous flood damages in Poland in 1997, in Germany, the Czech Republic and Slovakia in 2002, and also in China, the United States, Southern Africa and many other countries are well known. Although the reasons for the increasing frequency of extreme events are difficult to exactly recognize, some of them may be given: possible climate/weather fluctuations, increasing population and asset concentrations in flood-prone areas and improper land-use practices. Floods are not the strongest or the most sudden physical phenomena in the world. However, they appear to be the most disastrous events. We should not expect that this phenomenon will be inhibited by itself. On the contrary, it may be expected that floods become one of main development barriers for countries which are unable to cope with the problem. Thus, proper flood protection strategies become dramatically important.

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1. Introduction

Floods and water use have been linked together since ancient times. Rivers provide water and keep the society alive, but they also cause danger: they damage properties and even take lives. During the last few decades we can observe an unusual frequency of flood events. High flood losses are typical either for developed or developing countries. Examples of enormous flood damages in Poland in 1997, in Germany, the Czech Republic and Slovakia in 2002, and also in China, the United States, Southern Africa and many other countries are well known. Although the reasons for the increasing frequency of extreme events are difficult to exactly recognize, some of them may be given: possible climate/weather fluctuations, increasing population and asset concentrations in flood-prone areas and improper land-use practices. Floods are not the strongest or the most sudden physical phenomena in the world. However, they appear to be the most disastrous events. We should not expect that this phenomenon will be inhibited by itself. On the contrary, it may be expected that floods become one of main development barriers for countries which are unable to cope with the problem. Thus, proper flood protection strategies become dramatically important.

Flood defense systems consist of uncontrollable and controllable structures, e.g., dikes, polders and reservoirs linked to decision support systems which allow for a selection of proper ex-post controls. The controllable structures are designed on the basis of a long-term strategy taking into account economical, sociological and hydrological conditions in the prevented area. The problem was studied by many researchers and practitioners which can be identified from recent publications: Bachoc et al. (2000), Viljoen et al. (2001), Xia et al. (2001), Stevens et al. (2001), Plate (2001). The controllable structures deal with medium- and short-term strategies drawn up on the basis of the current state of the system. Various operational decision rules were analyzed, i.e., by Agthe et al. (2000), Takeuchi (2001), Shim et al. (2002), Islam and Sado (2002) and many others. The linkage between structures and controls is essential for the efficiency of a flood defense system.

In this paper the proper design of robust control rules for reservoirs under uncertain inflows is considered. The case study system chosen is the Nysa Klodzka basin. The system and the problem of flood losses in this basin are shortly introduced in Section 2. The importance of explicit treatment of inflow uncertainty is discussed in Section 3. Section 4 presents the deterministic approach to the control problem. The need for stochastic models and new approaches are discussed in Section 5. In Section 6 solutions for the most important computational problems are proposed. The simplified single reservoir case is studied in Section 7. Finally, some concluding remarks are presented in Section 8.

2. The case study system: the Nysa Klodzka basin

2.1 Description of the system

The water resources are not very big in Poland. The average annual rainfall over its territory is about 600 mm. However, the flood danger is very high, especially in mountain areas, where sudden extreme rainfalls may occur. In 1997 10% of Poland's territory was flooded causing economic losses of 2.9% of Poland's GDP. The annual precipitation in these regions is much higher then the average in Poland. Therefore, the case study area, the Nysa Klodzka basin in the southern part of the country is considered of high importance. This river is a tributary of the Odra, one of two biggest rivers in the country. The length of the catchment is 181.7 km and its area is 4565.7 km^2. It is one third of the Odra river basin in the junction of both rivers, which means it is the biggest tributary of the Odra in this region. The population and industry density in the catchment is very large. The safety of big cities like Wroclaw, Brzeg, Olawa depends on the flow conditions in these two rivers.

The annual rainfall in the case study region varies between 700-1200 mm. The wettest season is July, when precipitation is 100-140 mm. The rainfalls are often very quick and intensive. The resulting fast runoff causes a sudden increase of flow in rivers and channels. Floods are a very frequent phenomenon in the area. Since they are very sudden and wide-spread, such kinds of flood protection as building dikes or standard water management in reservoirs are very difficult to implement. During the control action taken to prevent floods the complexity of the system should be taken into account. Simple water management on the basis of engineering rules applied in existing reservoirs may secure the area located below the reservoirs. However, it may cause flood wave interaction in the junction of both rivers.

The system is shown in the Figure 2.1. It consists of two big channels: the Odra and its tributary, the Nysa Klodzka. Two big reservoirs are located on the tributary. These are the Otmuchow (the upper one) and the Glebinow (the lower). Their storages are about 100 million m^3 (Table 2.1). The main goals of the system are flood protection during wet seasons and water supply with production of hydroelectric power during the rest of the year. The inflows to the system are determined on the basis of measurements or precipitation forecasts from the net of meteorological and hydrological stations. The chain of inflows consists of the main inflow to the upper reservoir, aggregated lateral inflow to the lower one, flow in the Odra river and lateral inflow along the Nysa Klodzka channel below the reservoirs. The outflows from the reservoirs are controlled. The outflow from the lower reservoir is transformed in the flow in Nysa Klodzka outlet.

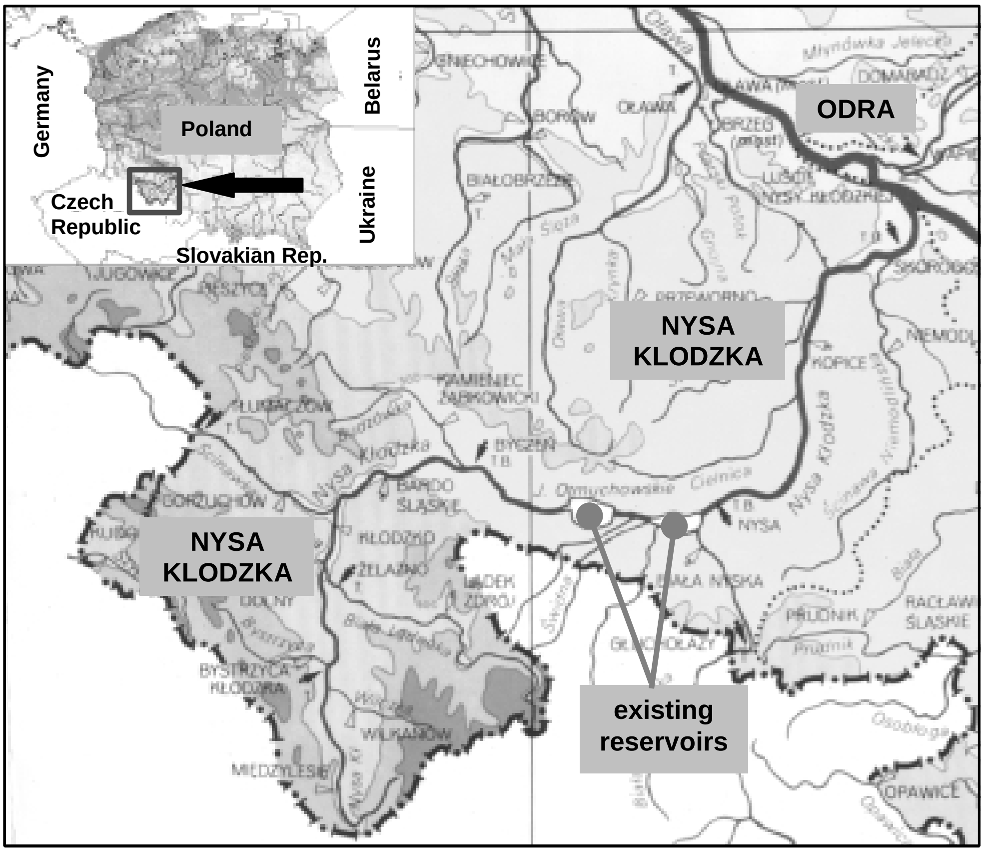

Figure 2.1. Nysa Klodzka catchment

2.2 The flood defense system

The most dangerous situation in the system is flood waves interaction in the junction of both rivers. If extreme flow peaks occur in the junction at the same time, the severe flood threatens the main water users in the system located below the junction. Such an event took place in 1997, when a severe flood damaged Wroclaw, one of the biggest cities in Poland, and many other cities and villages. Inappropriate control of reservoirs caused interaction of flow peaks. The resulting maximum flow below the junction was over 3000 m^3/s (Figure 2.2).

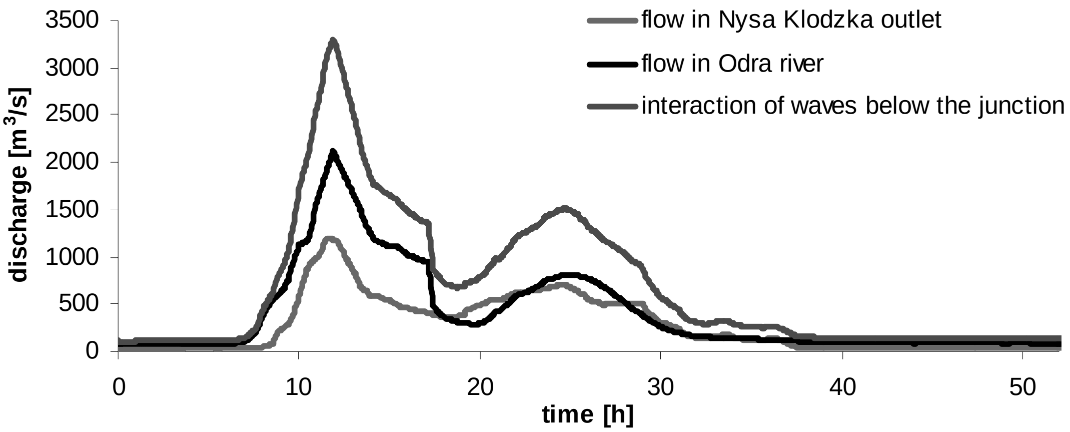

Figure 2.2 Flood wave interaction in 1997

The Flood Defense System in the case study area consists of controllable reservoirs. They should be linked by proper control strategies (decisions). This linkage is essential for the effectiveness of the defense system, since inappropriate controls may cause floods and losses. The main parameters of two existing reservoirs are shown in Table. 2.1. Currently outflows are selected on the basis of simple engineering rules based on current storage and short-term inflow forecast. Unfortunately the existing system is not able to prevent floods similar to the flood in 1997. Therefore, two additional reservoirs with similar capacity are built and a fifth reservoir is planned, which will be located above the current upper reservoir. For the effectiveness of the whole system the design of an appropriate decision support system, which enables selection of optimal controls, is necessary.

Table 2.1

Reservoirs' capacity and releases

RESERVOIRS PARAMETERS	OTMUCHOW	GLEBINOW
Reservoir Capacity [10^6 m^3]		
emergency storage	9,64	6,0
useful capacity*:*	76.18	79.68
flood capacity*:*		
constant flood capacity	15,27	27,92
strenuous *flood capacity*	23,37	–
total capacity	124,46	113,60
Maximum Outflow [m^3/s]	1363,0	1960,0

The decision support system consists of methods which can be divided into two main groups: inflow forecasts and control algorithms. The main parts of inflow prediction are precipitation forecast and rainfall-runoff transformation models. The precipitation part relies on a global circulation model linked to statistical downscaling procedures. The rainfall-runoff part is formed by physically based or conceptual models. On the basis of these algorithms the meteorological and hydrological forecast is composed. The main parts of the control algorithms are flow transformation models and optimization procedures. The decisions are selected on the basis of inflow measurements or forecasts and predicted effects in the system.

Precipitation and runoff are the phenomena which are still not well recognized. These processes are very complex, since many factors influence them. Only some of them are known and investigated. For this reason decision makers are not able to rely a 100% on forecasts and must take existing uncertainties into account. This is discussed more extensively in Section 3.

The main problem concerns the explicit treatment of uncertainties regarding the inflows to the reservoir system. Stochastic optimization may be applied as a part of the control module. In this case the data provided by the forecast module should consist of inflow forecast, its validity and possible range of changes. In other words, the inflow forecast should be formulated in a probabilistic sense. The main aim of this paper is to develop a procedure which enables the control of the reservoir system under uncertain inflows.

3. Treatment of uncertainties

3.1 Current state of inflow forecasting

As was mentioned in Section 2, the decision support system for flood control in the case study area consists of an inflow forecast module and control algorithms. The results produced by the forecast module are the basis for the selection of controls. Though the problem of inflow forecasting is not the subject of the research presented, a short overview would be useful for a clear understanding of the main problem, the stochastic control of reservoirs. The inflow prediction module may consist of two parts: precipitation forecast and rainfall-runoff transformation model. These parts form a meteorological and hydrological forecast. Sometimes one of the flow routing models described in Section 4 is an additional element of the hydrological part.

The precipitation forecast is based on so-called global circulation models (GCMs) and downscaling techniques. GCMs are well known models describing the evolution of global weather variables such as temperature, pressure and moisture, wind strength and wind direction. The governing equations are mass, momentum and energy balance equations. Since the GCMs operate with a small resolution, they are not used to describe local weather changes. For this purpose downscaling techniques are used. It is possible to indicate three main approaches to the problem: dynamical downscaling, stochastic downscaling and stochastic weather generators (Prudhomme et al., 2002, Prudhomme et al., 2003).

The dynamic downscaling is based on the same kind of physical laws as global circulation models, but the resolution is much finer. Such techniques were investigated by Jones et al., (1995), Murphy (1999), Bates et al. (1998) and many others. This approach allows to include subregions which are not represented in the GCM grid. The processes nested in GCMs provide boundary conditions for this kind of downscaling, which is also called Regional Climate Models or Limited Area Models. In statistical downscaling relationships between large-scale climate features and regional characteristics are used to produce future scenarios. Examples of such an approach may be found in Burger (1996), Conway and Jones (1998), Sailor et al. (2000), Stehlik and Bardossy (2002), Wilby et al. (2002). The range of summary statistics that could be provided by the GCM output is used to create sub-daily weather series in the third approach, stochastic weather generators. Some results were provided by Semenov and Barrow (1997), Schnur and Lettenmaier (1998), Wilks (1999), Goodsell and Lamb (1999) and others.

The second stage model of inflow forecast is rainfall-runoff transformation. According to the classification proposed by Beven (1985) and used by Yu and Jeng (1997) there are two basic types of rainfall-runoff models: the kinematic wave approach and the conceptual storage approach. The first is physically based on mass and momentum balance principles. It was studied by Eagelson (1972), Jønch-Clausen (1979), Abbott et al. (1986), Morris (1980), Edward et al. (1977), Ross et al. (1979), Jayawardena andWhite (1977, 1978), Osuch (2003) and others. The desired runoff is obtained by the solution of the partial differential equation. The boundary condition is provided by the measured or predicted rainfall. The main assumption here is that the real area may be modeled as system with a uniform slope. Such an ideal approach is not always possible, even if we postulate the use of equivalent parameters in the governing equation, which replace the original ones. In the second group of models the real system is replaced by an approximate one. Some examples may be found in Laurenson (1964), Ibbitt and O'Donnell (1971), Ciriani et al. (1977), Diskin and Simpson (1978), Diskin et al. (1984), Knudsen et al. (1986), Szymczak (2003). In this approach particular processes in the basin are replaced by specifically designed reservoir cascades. They may also be represented by a specially calibrated unit hydrograph function.

3.2 Uncertainties in precipitation and runoff modeling

Uncertainty is almost always involved in any comprehensive management task. Since our knowledge about the nature is limited, taking into account uncertainty is essential in environmental problems. According to Hulme and Carter (1999) we can specify two different sources of uncertainties, the so-called 'incomplete' knowledge and the 'unknowable' knowledge. The first is included in model design affected by our knowledge about the process and ability to describe the phenomenon properly in mathematical terms. We can expect that further development of science and modeling may reduce this kind of uncertainty. The second source, 'unknowable' knowledge, is the indeterminacy of the future human society and climate system. Human actions like greenhouse gas emissions and changes of land cover are not predictable in the deterministic sense. We are only able to predict main trends in the future on the basis of past events and expert opinions, which only allows for the generation of possible scenarios. No exact predictions are possible.

The advantage of Regional Climate Models is their physical basis. However, they are still dependent on signals included in their boundary conditions provided by an inaccurate Global Circulation Model. The accuracy of statistical downscaling is much lower since the algorithms are simpler and the set of the relationships considered between large scale and local weather parameters is subjectively selected. In addition, this approach is based on the assumption that present relationships between large-scale and local parameters remain unchanged in the future. Such assumption leads to uncertain errors in the presence of global and local climate changes. Similar problems affect the use of stochastic weather generators (Prudhomme et al., 2003).

If the rainfall is uncertain, the results of runoff model cannot be exact either. Another source of uncertainty in the rainfall-runoff transformation is the current state of the system. Especially the intensity of infiltration is an important factor. It depends on the previous rainfalls. The simple calibration of rainfall-runoff models on the basis of past recorded data represents the next uncertainty source. Land-use changes make an exact deterministic calibration completely useless. The set of integrated parameters included in the model is sufficient for the past state of the system, but it should be calibrated once again after change. In many cases data which describe the new changed system do not exist and the most important approach is again an explicit treatment of uncertainties.

3.3 Desirable forecast for the stochastic control of the reservoirs system

On the basis of the techniques mentioned shortly in subsections 3.1 and 3.2, long-, medium- and short-term forecasts are formulated. The two first kinds of forecast techniques provide averaged parameters in a specified time horizon whose length varies from decades to years. Even a decade time horizon is much longer than the time step which has to be considered in the presence of flood. For this reason hourly and daily short-term forecasts are used for flood management. However, their accuracy is still not sufficient and we have to assume some range of the uncertainty. A proper uncertainty model is very important for realistic conclusions. The desired inflow forecast for flood control of the reservoir system should consist not only of the predicted course of the flood, but also of its validity and possible range of changes. As far as possible the probability should be assigned to inflow scenarios. In the other case the inflow scenarios may be considered uniformly distributed.

The stochastic inflow generating problem has quite a long history. One of the first results was publicized by Thomas and Fiering (1962). A stochastic approach for water supply reservoir control with many inflow scenarios excluding catastrophic floods was proposed, i.e., by Willen (1979).

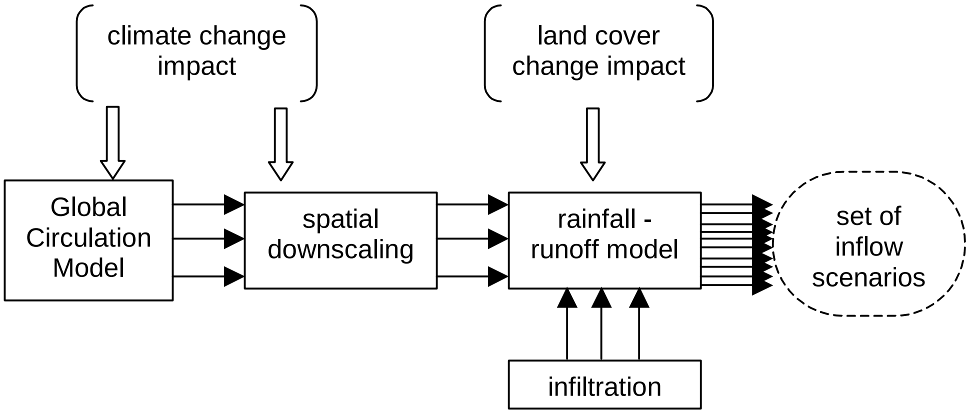

Figure 3.1 Generation of inflow scenarios: use of deterministic models

The set of possible inflow scenarios may be generated by sophisticated deterministic models described in Sections 3.1 and 3.2 (Figure 3.1). The main sources of the uncertainties are easily identified. The first source is the GCM output or weather measurement. The GCM downscaling output is the rainfall-runoff model input. The value of current infiltration is another source of uncertainty in the process. We can imagine also that GCM output is not treated as deterministic. Instead of an exact determination of climate variables such as temperature, pressure, etc. their probability distributions should be determined. A similar approach may be implemented in the case of infiltration. On this basis a wide range of possible inflow scenarios might be generated. Even the changes of the model parameters may be taken into account. Some studies of the impact on the climate and land cover changes on the flood regime are discussed by Wood (1974), Katz (1999), Muller-Wohlfeil et al. (2000), Prudhomme et al. (2003).

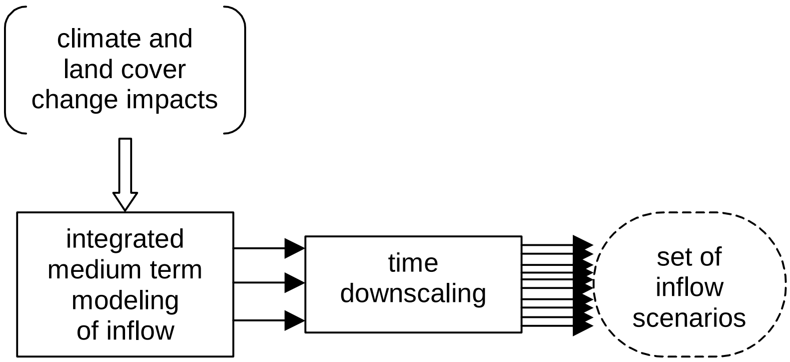

Figure 3.2 Generation of inflow scenarios: medium- term forecast and time downscaling

Another approach is based on the special design of the inflow forecast (Figures 3.2 and 3.3). Approximate medium-term forecast for pentads, weeks or decades may be defined by some informative events ("something happened") in a certain period of time, e.g., when extreme flow peaks occurs. If this information is downscaled in time, it would lead us to so-called unconditional time downscaling described in Bierkens et al. (2000). This approach may be suggested for generating hourly scenarios from averaged pentad or decade inflows. A similar method for stochastic generation of runoff series was used by (Willen, 1979). The following Figure 3.3 illustrates the main idea. We can assume a continuous function which describes the flood wave course, e.g., the Reitz-Kreps function as used in many engineering applications. The form of such a function may be specified on the basis of historical data describing floods in selected river cross-sections. The parameters of the function may be calibrated for the given averaged inflows in subsequent periods of time. If the averaged inflows are not specified exactly, but are determined as ranges of possible variations, many possible functions are feasible. Accordingly we determine a number of inflow scenarios. The main conditions which should be satisfied are equalities of water volume obtained from forecasts and downscaling. Therefore the integrals of calibrated functions have to be approximately equal to the integrals of the predicted averaged inflows in given time intervals.

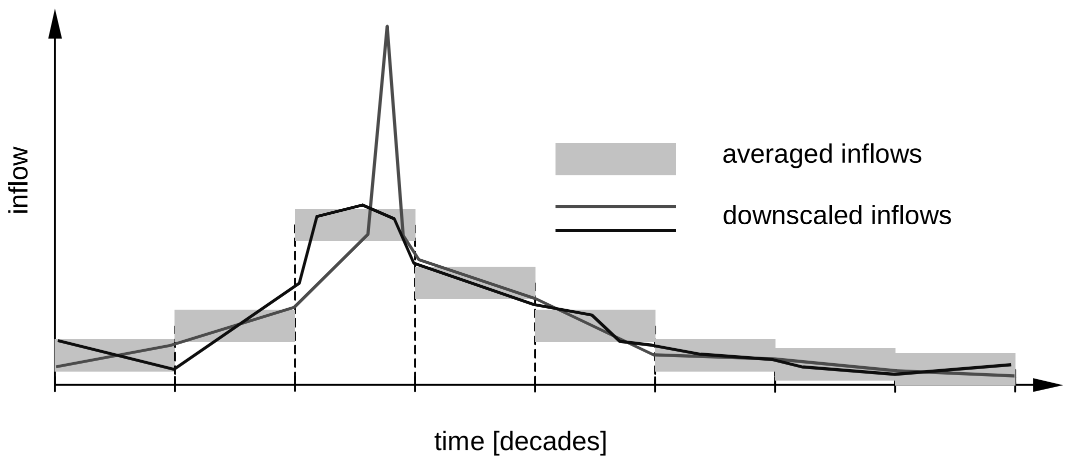

Figure 3.3 Main concept of time downscaling for inflow forecasting

In this paper it was assumed that generated inflow scenarios are available. Our main purpose is to analyze how these data can be used for control algorithms. This is described in Section 5.

4. Control of a reservoir system: deterministic approach

4.1 Reservoir state equations and constraints

First of all, let us outline the deterministic case. The control system is shown in Figure 4.1. It consists of N reservoirs in series and long channel reach which connects the system with the end-users. The inflows $I_1, I_2, \ldots I_{N+1}$ are determined on the basis of measurements or forecast. Each reservoir outflow $u_1, u_2, \ldots u_N$ is controlled. Reservoir storages $V_1, V_2, \ldots V_N$ should not exceeded the admissible minimum $V_{\min j}$ and maximum $V_{\max j}$ values (for $j = 1, 2, \dots N$) at any moment $t \in [0, T_H]$ where T_H is a given time horizon. Similar constraints are set for reservoir outflows: $U_{\min j} \le u_j \le U_{\max j}$ for any $j = 1, 2, \dots N$ and $t \in [0, T_H]$. Since channels connecting reservoirs are very short, we can assume that each outflow u_j for $j = 1, 2, \dots N - 1$ is the second inflow to the lower reservoir j+1. Only the outflow from the last reservoir u_N is transformed in the long channel reach. This transformed flow with lateral inflow along the channel $q(x, t)$ forms the flow Q_r in the outlet of the reach. The flow in the end-users' area is summarized as outflow from the reach Q_r and last inflow to the system I_{N+1}.

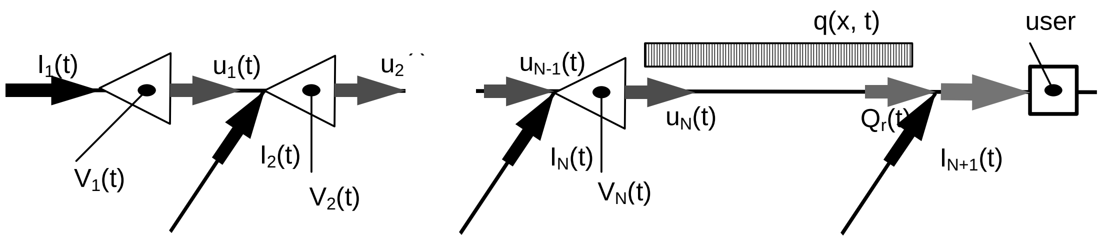

Figure 4.1 System of reservoirs in series

The system dynamics is described by mass and momentum balances principles. The reservoir equations may be written in the linear form as follows

$$\frac{dV_1}{dt} = I_1 - u_1, \tag{4.1}$$

$$\frac{dV_j}{dt} = u_{j-1} + I_j - u_j, \qquad j = 2, 3, \dots N \tag{4.2}$$

with initial conditions $V_j(0) = V_{j0}$ for $j = 1, 2, \dots N$. Equations (4.1) - (4.2) are also expressed in the nonlinear form

$$\frac{dh_1}{dt} = \frac{I_1 - u_1}{F_1(h_1)}, \tag{4.3}$$

$$\frac{dh_j}{dt} = \frac{u_{j-1} + I_j - u_j}{F_j(h_j)}, \qquad j = 2, 3, \dots N \tag{4.4}$$

where h_j is the water level of the j^{th} reservoir and $F_j(h_j)$ is the water surface area. However, equations (4.1) - (4.2) are more useful for our purpose, since we are able to determine the amount of accessible water directly from (4.1) - (4.2). This is the main task of many water management problems. The first set of equations is especially important when we deal with explicit treatment of uncertainties.

The constraints set on control and state variables have the form

$$U_{\min j} \le u_j \le U_{\max j}, \qquad V_{\min j} \le V_j \le V_{\max j} \tag{4.5}$$

and in a deterministic model should be satisfied for each $t \in [0, T_H]$ and $j = 1, 2, \dots N$. If the dynamics of the reservoir system is described by (4.3) - (4.4), the values $U_{\min j}$ and

$U_{\max j}$ depend on water level h_j in the reservoir. However, in a simple linear case we may assume they are constant.

4.2 Unsteady flow transformation models

The flow channel reach transformation model from the last reservoir may be written in a general form as

$$Q_r(t) = \Psi[u_N, q](t) \tag{4.6}$$

where $\Psi[u_N, q]$ represents one of the following well-known (Chow,1959; Cunge et al. 1980) open channel flow models:

a. Dynamic wave (de Saint-Venant equations).

$$\frac{\partial H}{\partial t} + \frac{1}{B}\frac{\partial Q}{\partial x} = q\,, \tag{4.7}$$

$$\frac{\partial Q}{\partial t} + \frac{\partial}{\partial x}\left(\frac{Q^2}{A}\right) + gA\frac{\partial H}{\partial x} = gA(S_0 - S_f)\,, \tag{4.8}$$

The independent variables are x and t, which represent space and time, respectively. Dependent variables are functions: $Q(x, t)$ - discharge and $H(x, t)$ - water depth. The set of (4.7) and (4.8) is completed by initial and boundary conditions. For each $x \in [0, L]$ the initial state of the flow should be known: $Q(x, t = 0) = Q_P(x)$ and $H(x, t = 0) = H_P(x)$. In the most practical cases the condition $v/\sqrt{gH} < 1$ (v is average speed of flow in cross - section, $v = Q / A$) is satisfied. Then boundary conditions are as follows: for each $t \geq 0$ the inflow to the reach is equal to the outflow from the reservoir system $Q(x = 0, t) = u_N(t)$ and the relationship between discharge and water depth is postulated in the last cross-section of the channel $F[Q(x = L, t), H(x = L, t)] = 0$.

b. Diffusive wave.

This model is such a simplification of (4.7) - (4.8) that inertia terms are neglected:

$$\frac{\partial H}{\partial t} + \frac{1}{B}\frac{\partial Q}{\partial x} = q\,, \tag{4.9}$$

$$\frac{\partial H}{\partial x} = S_0 - S_f\,. \tag{4.10}$$

The validity of such a procedure was proved by Henderson (1966). The set of equations (4.9) - (4.10) may be rewritten in a few different forms. One of them is shown below

$$\frac{\partial Q}{\partial t} = \frac{K^2}{2|Q|}\frac{\partial}{\partial x}\left[\frac{1}{B}\left(\frac{\partial Q}{\partial x} - q\right)\right] - \frac{Q}{KB}\frac{\partial K}{\partial H}\left(\frac{\partial Q}{\partial x} - q\right) \tag{4.11}$$

$$\frac{\partial H}{\partial x} = S_0 - S_f \tag{4.12}$$

The equations (4.9) - (4.10) are completed by the same initial and boundary conditions as set (4.7) - (4.8).

c. Kinematic wave.

This model is also a simplification of the de Saint-Venant equations (4.7) - (4.8). Inertia and pressure terms are neglected, which leads to

$$\frac{\partial H}{\partial t}+\frac{1}{B}\frac{\partial Q}{\partial x}=q\,, \tag{4.13}$$

$$S_0=S_f\,. \tag{4.14}$$

The model may be simplified to the nonlinear advection equations form

$$\frac{\partial Q}{\partial t}+\frac{Q^{1-m}}{\alpha\, m}\frac{\partial Q}{\partial x}=\frac{Q^{1-m}}{\alpha\, m}q\,. \tag{4.15}$$

In such a case initial and boundary conditions are: for $x \in [0, L]$ searched function is $Q(x, t = 0) = Q_P(x)$ and for $t \geq 0$ inflow to the reach is equal the outflow from the reservoir system $Q(x = 0, t) = u_N(t)$.

In equations (4.7) - (4.15) $A[H(x, t), x]$ is the cross-section area, $B[H(x, t), x]$ - the width of the channel, g - gravity acceleration equal to 9.81 m/s^2. $S_0(x)$ and $S_f[Q(x, t), H(x, t), x]$ are bottom and friction slopes, respectively. $q(x, t)$ is the lateral inflow along the channel, $K[H(x, t), x]$ is module flow. α and m are parameters derived from empirical formulas or determined on the basis of optimization.

In some cases constraints may be set on water levels in the important cross - sections of the channel:

$$H(x_l, t) \leq H_{\max\, l}\,, \qquad \text{for } t \in [0, T_H]\,. \tag{4.16}$$

Formula (4.16) is used for selected x_l ($l = 1, 2, \ldots$). Obviously, all water levels have to be greater than or equal to zero $H(x, t) \geq 0$ for all $t \in [0, T_H]$ and all $x \in [0, L]$.

4.3 Control criterion

In the case of floods the most important goal of the control is the flood protection of the main water users in the system. Under deterministic inflow forecast this aim may be expressed as a minimization of the flow peak below the last inflow to the system. If the reservoir system is also used as a water supply source during the drier periods of the year, the second goal may be formulated as the water storing at the end of the time horizon. This can be written as a minimization of the difference between the maximum storage of the reservoir and its storage at the end of the control horizon T_H. Thus we can formulate the problem as one scalar criterion

$$f(\mathbf{u},\mathbf{I},q,t)=\max_{t\in[0,T_H]}[Q_r(t)+I_{N+1}(t)]+\beta\lambda\sum_{j=1}^{N}[V_j(T_H)-V_{\max\, j}]^2\,, \tag{4.17}$$

where β is the coefficient which determines the significance (trade-offs) of criterion parts and λ is the scale coefficient. The dependence of (4.17) on controls is implicit. The state equations (4.1) - (4.2) connect storages with outflows. The optimal set of controls $\mathbf{u} = [u_1(t), u_2(t), \ldots u_N(t)]$ should minimize (4.17) for given inflows $\mathbf{I} = [I_1(t), I_2(t), \ldots I_{N+1}(t)]$ and $q(x, t)$.

5. Stochastic optimization problem

5.1 General formulation of the problem

Optimization problems with random parameters may be written symbolically as follows (Ermoliev & Wets, 1988):

find $\mathbf{u} \in U \subset R^m$

such that $f_i(\mathbf{u}, \boldsymbol{\omega}) \leq 0$ for $i = 1, 2, \ldots n$ (5.1)

and for each $\boldsymbol{\omega} \in \Omega \subset R^q$, $z_{\boldsymbol{\omega}} = f_0(\mathbf{u}, \boldsymbol{\omega})$ is minimized (5.2)

where $\mathbf{u}$ is the vector of control variables and $\boldsymbol{\omega}$ is an unknown vector of random variables. Set Ω consists of probable $\boldsymbol{\omega}$ elements. This set and its elements are the parts of the probabilistic space $(\boldsymbol{\omega}, \Omega, P)$ where $P(\mathbf{d}\boldsymbol{\omega})$ is the probability of event $\boldsymbol{\omega}$ determined in domain Ω. Constraints (5.1) and the objective function (5.2) may depend on random $\boldsymbol{\omega}$ variables. Since constraints may not be satisfied for some sampled $\boldsymbol{\omega}$ and the objective function can not be minimized for all $\boldsymbol{\omega}$, the problem (5.1), (5.2) has to be properly formulated.

To formulate exactly the problem (5.1) - (5.2) one has to consider depending on a concrete application of a wide range of exact statements of the above problem, according to specifying in which sense function (5.2) is minimized and constraints (5.1) are satisfied. The simplest model is to average random variable

$$\overline{\boldsymbol{\omega}} = \int_{\Omega} \boldsymbol{\omega} P(\mathbf{d}\boldsymbol{\omega}) \quad (5.3)$$

where $\overline{\boldsymbol{\omega}}$ is the average value of $\boldsymbol{\omega}$ in Ω and $P(\mathbf{d}\boldsymbol{\omega})$ is the probability distribution associated with uncertainties in the Ω set. This is common practice in standard deterministic models. In many cases such simplification does not lead to reasonable results.

Among other approaches two of them are most common. A certain level of safety is assumed in the first case. The problem is formulated as follows (Ermoliev & Wets, 1988):

find $\mathbf{u} \in U \subset R^m$

such that $P\{f_i(\mathbf{u}, \boldsymbol{\omega}) \leq 0\} \geq \alpha_i$ for $i = 1, 2, \ldots n$ (5.4)

and $P\{f_0(\mathbf{u}, \boldsymbol{\omega}) \geq \alpha_0\}$ is minimized (5.5) where P(.) is probability of such an event that the random sample objective function $f_0(\mathbf{u}, \boldsymbol{\omega})$ should not exceed a given "safety" level α_0 subject to constraints. α_i (i = 1, 2, … n) are assumed to be the desirable levels of reliability. Therefore in this case the optimal solution **u** should guarantee that the constraints (5.1) are not violated with probability α_i.

The model (5.4) - (5.5) causes in many cases additional problems. The objective function (5.5) and constraints (5.4) may not be convex, even if the original random sample functions $f_0(\mathbf{u}, \boldsymbol{\omega})$, $f_i(\mathbf{u}, \boldsymbol{\omega})$ are convex and even linear with respect to **u**. For many applications a different approach based on averaging of stochastic objective function and constraints can be used. The optimization problem in this case is formulated as follows (Ermoliev & Wets, 1988):

find $\mathbf{u} \in U \subset R^m$

such that $E_{\boldsymbol{\omega}}[f_i(\mathbf{u},\boldsymbol{\omega})] \le 0$ for i = 1, 2, … n (5.6)

and $E_{\boldsymbol{\omega}}[f_0(\mathbf{u},\boldsymbol{\omega})]$ is minimized. (5.7)

$E_{\boldsymbol{\omega}}$ is the mean value of $f_0(\mathbf{u}, \boldsymbol{\omega})$, i.e. for any random function $\varphi(\,.\, , \boldsymbol{\omega})$ depending on random variable $\boldsymbol{\omega} \subset \Omega$ it is determined as

$$E_{\boldsymbol{\omega}}[\varphi(\,.\,,\boldsymbol{\omega})] = \int_{\Omega} \varphi(\,.\,,\boldsymbol{\omega}) P(\mathbf{d}\boldsymbol{\omega})\,. \tag{5.8}$$

Let us note that for non-linear in **u** stochastic functions $f(\mathbf{u},\boldsymbol{\omega})$ the average value of $f(\mathbf{u},\boldsymbol{\omega})$ is not equal $f(\mathbf{u},\overline{\boldsymbol{\omega}})$, i.e. the model (5.6), (5.7) significantly differs from the standard deterministic models.

The formulation of the control of the flood defense system problem is based on these two approaches. However, they are not applied directly. The complexity of the task considered involves some other modifications, which are described in subsequent parts of this section.

5.2 Straightforward application and its disadvantages

Assuming that initial state of the system $\mathbf{V}(0) = \mathbf{V}_0$ is exactly known, state equations (4.1) - (4.2) enable evaluation of reservoir storages $V_j(t)$ (j = 1, 2, … N) in any $t \in [0, T_H]$ for a certain set of reservoir inflows $I_j(t)$ and outflows $u_j(t)$ (j = 1, 2, … N). This allows us to consider the problem discussed in Section 3 as a stochastic optimization problem dependent on random inflows ($\boldsymbol{\omega}$ variables) and controlled outflows. Following the straightforward formulation (5.6), (5.8) we can write the reservoir system control problem as follows

find $\mathbf{u}(t) \in U(t)$

such that for i = 1, 2, … N

$$E_{\mathbf{I}(t)}\left[\int_0^{T_H} \max(0, U_{\min j} - u_j)dt\right] \le \varepsilon_u \qquad E_{\mathbf{I}(t)}\left[\int_0^{T_H} \max(0, u_j - U_{\max j})dt\right] \le \varepsilon_u \tag{5.9}$$

$$E_{\mathbf{I}(t)}\left[\int_0^{T_H}\max(0, V_{\min j} - V_j)dt\right] \le \varepsilon_V \qquad E_{\mathbf{I}(t)}\left[\int_0^{T_H}\max(0, V_j - V_{\max j})dt\right] \le \varepsilon_V \quad (5.10)$$

and

$$E_{\mathbf{I},q}\left\{\max_{t\in[0,T_H]}[Q_r(t) + I_{N+1}(t)] + \beta\lambda\sum_{j=1}^{N}[V_j(T_H) - V_{\max j}]^2\right\} \quad \text{is minimized.} \qquad (5.11)$$

The constraints (4.5) are formulated in average integral form, where ε_u and ε_V are small positive numbers which determine the acceptable level of average constraint violation. This is compatible with model (5.6) - (5.8) but in practice the constraints on reservoir storages and outflows must not be violated for extreme situations. If this happens, the dam-break problem should be considered instead of flood damages, i.e., higher losses are involved than the losses caused by flood.

5.3 Two-stage recourse model: robust control strategy

The problem of constraints violation introduced may be overcome by application of stochastic optimization models with recourse actions (Ermoliev & Wets, 1988). Let us consider problem (5.2) with constraints (5.1). We can present the control variable as the combination of anticipative action taken in advance $\mathbf{u}'$ and adaptive action $\mathbf{u}''$ selected when first information (measurements) about $\boldsymbol{\omega}$ are available.

Now, the stochastic optimization problem (5.6) with (5.7) may be written as

find $\mathbf{u}' \in U' \subset R^m$

such that $\qquad E_{\boldsymbol{\omega}}\{g_0[\mathbf{u}', \mathbf{u}''(\mathbf{u}', \boldsymbol{\omega}), \boldsymbol{\omega}] + q[\mathbf{u}''(\mathbf{u}', \boldsymbol{\omega}), \boldsymbol{\omega}]\}$ is minimized (5.12)

where $g_0[\mathbf{u}', \mathbf{u}''(\mathbf{u}', \boldsymbol{\omega}), \boldsymbol{\omega}]$ is defined as optimal objective function value of the problem:

for given $\mathbf{u}'$ find $\qquad \mathbf{u}'' \in U'' \subset R^m$

such that $\qquad f_i(\mathbf{u}, \boldsymbol{\omega}) \le 0$ for $i = 1, 2, \dots n$ (5.13)

and for each $\boldsymbol{\omega} \in \Omega \subset R^q$, $\qquad z_{\boldsymbol{\omega}} = f_0(\mathbf{u}, \boldsymbol{\omega})$ is minimized, (5.14)

where $\mathbf{u}$ is determined as a function of $\mathbf{u}'$ and $\mathbf{u}''$

$$\mathbf{u} = \rho(\mathbf{u}', \mathbf{u}''), \qquad (5.15)$$

In (5.12) function $q[\mathbf{u}''(\mathbf{u}', \boldsymbol{\omega}), \boldsymbol{\omega}]$ describes the aggregated cost of recourse action. In important cases the cost of recourse action may be formulated as

$$q[\mathbf{u}''(\mathbf{u}', \boldsymbol{\omega}), \boldsymbol{\omega}] = \sum_{j=1}^{m}(u_i'')^2 \qquad (5.16)$$

5.4 Application of a two-stage recourse model for the reservoirs control problem

Fortunately, in the analyzed case of flood protection we are able to implement a very simple combination of $\mathbf{u}'$ and $\mathbf{u}''$ as desired control $\mathbf{u}$:

$$\mathbf{u} = \mathbf{u}' + \mathbf{u}'' \tag{5.17}$$

which leads us to a modified version of (4.1) and (4.2)

$$\frac{dV_1}{dt} = I_1 - (u_1' + u_1'') \tag{5.18}$$

$$\frac{dV_j}{dt} = (u_{j-1}' + u_{j-1}'') + I_j - (u_j' + u_j''), \quad j = 2, 3, \ldots N. \tag{5.19}$$

Now the flow transformation model has the form

$$Q_r(t) = \Psi[u_N' + u_N'', q](t)\,. \tag{5.20}$$

The application of a recourse model as discussed in 5.3 by taking into account (4.17) leads to two optimization levels

$$\min_{\mathbf{u}'\in U'} E_{(\mathbf{I},q)} \left\{ \min_{\mathbf{u}''\in U''} f[\mathbf{u}' + \mathbf{u}''(\mathbf{u}', \mathbf{I}, q), \mathbf{I}, q, t] + \beta_2 \sum_{j=1}^{N} \int_0^{T_k} [u_j''(t)]^2\, dt \right\}, \tag{5.21}$$

where objective function from (4.17) $f[\mathbf{u}' + \mathbf{u}''(\mathbf{u}', \mathbf{I}, q), \mathbf{I}, q, t]$ is minimized according to constraints (4.5)

$$U_{\min j} \le u_j' + u_j'' \le U_{\max j}\,, \qquad V_{\min j} \le V_j \le V_{\max j}\,, \tag{5.22}$$

This model allows us to avoid constraint violation, due to the flexible control actions. First of all, we are able to prepare the system before the flood occurs, which is achieved by proper selecting of the first stage controls $\mathbf{u}'$. The second term in (5.20) expresses the need of small changes at the second stage by choice $\mathbf{u}''$ which is compatible with decision makers' expectations in practice.

6. Computational complexity of the problem

6.1 Representation of reservoir outflow

The problem formulated in Sections 4 and 5 is defined in continuous function space. The controls and state equations are functions of time or time and space (lateral inflow along the channel). The problem in general can be viewed as a dynamic stochastic optimization task. Unfortunately, the important Bellman' dynamic programming equations and Pontriagin's maximum principle are not applicable for our model. The first of them enables the decomposition of the problem, if the objective function is separable in time. The second is applied in differentiable deterministic cases. the minmax-type criterion of the problem (5.17) - (5.20) is neither separable nor differentiable. The complexity is also associated with continuous time equations. These equations may be replaced by approximate discrete time equations but such a direct approximation causes an enormous dimensionality.

A reasonable step seems to be the replacement of continuous controls $u_j(t)$ by their parametric representation. Due to the state equations the reservoirs storages and outflow from the channel depends also on control parameters. The representation of the outflow should be selected in such a way that the number of parameters is not very big, but the choice of the decision rules must be consistent with the real performance of the system. The proper form of parameterization can be chosen as a chain of time dependent rectangular pulses shown in Figure 6.1 (Dysarz and Napiórkowski, 2002a). Each reservoir outflow in the system is represented by parameters $\alpha_1, \alpha_2, \ldots \alpha_{Np-1}$ where the first Np-1 parameters describe the length of time interval with constant value of outflow. The rest of the parameters describe the value of constant outflows according to Figure 6.1. Np is the number of determined pulses.

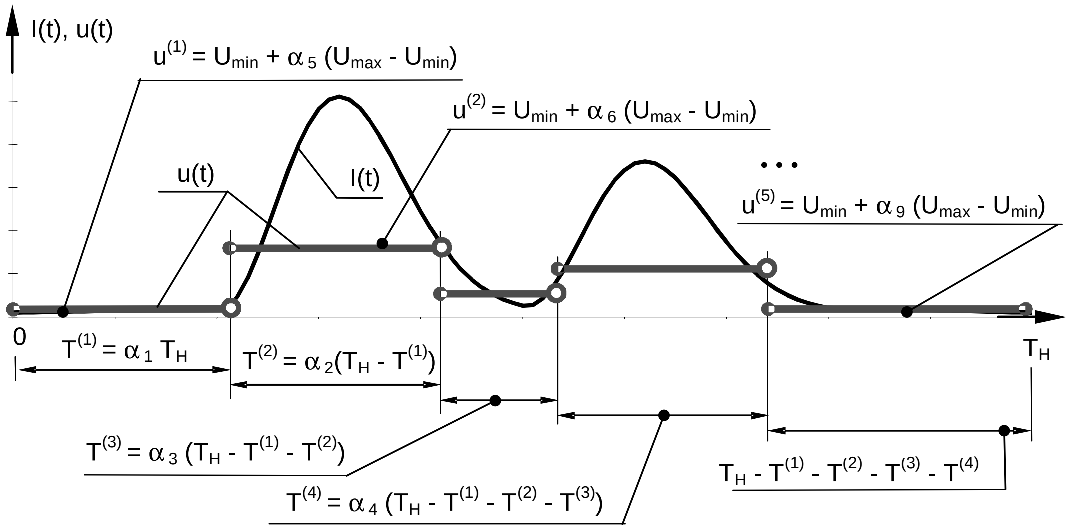

Figure 6.1 Rectangular pulse-type representation of the reservoir outflow

6.2 Sequential optimization technique

Although such a representation of the outflow is useful, it still leads to a large-scale optimization problem. Taking into account the huge reservoirs' capacity, the control horizon should be 100 to even 800 hours. Due to sudden changes in the system during the flood, proper decisions should be made hourly, which leads to large scale optimization problems. The next step which allows decreasing the computational efforts is the decomposition of the problem. Such an approach leads to the application of a sequential optimization algorithm which is implemented on the basis of the specific features of the system. The proposed procedure is based on a paper by Dysarz and Napiórkowski (2002b). The main idea is the following.

Let us assume that there is a known admissible solution of the problem (4.1) - (4.2) with (4.5) and (4.6) for a certain set of inflows $I_1, I_2, \ldots I_{N+1}$. This solution is denoted as $u_1^{(k)}$, $u_2^{(k)}$, … $u_N^{(k)}$. According to the state equations (4.1) - (4.2) we can find storages which match the controls $V_1^{(k)}$, $V_2^{(k)}$, … $V_N^{(k)}$. At the current step k+1 we are going to improve the control criterion value (4.17) by modifying only one storage $V_l^{(k+1)}$. The rest of the storages in the system $V_j^{(k+1)}$ (for j = 1, 2, … N and $j \neq l$) are fixed like they were at step k. We can achieve this by selecting a new value of l^{th} outflow, $u_l^{(k+1)}$. The rest of outflows in the system is modified according to equations (4.1) - (4.2). Under the assumption $V_j^{(k+1)} = V_j^{(k)}$ for $j \neq l$, the state equations have the form

$$\frac{dV_j^{(k+1)}}{dt} = \frac{dV_j^{(k)}}{dt} \qquad \Rightarrow \qquad I_1 - u_1^{(k+1)} = I_1 - u_1^{(k)} \quad \text{for } j = 1 \tag{6.1}$$

or

$$u_{j-1}^{(k+1)} + I_j - u_j^{(k+1)} = u_{j-1}^{(k)} + I_j - u_j^{(k)} \quad j = 2, 3, \dots N \tag{6.2}$$

with the exception of $j = l$. Such a simplification leads to

$$u_j^{(k+1)} = u_j^{(k)} + (u_l^{(k+1)} - u_l^{(k)}),\ j > l \tag{6.3}$$

$$u_j^{(k+1)} = u_j^{(k)},\ j < l \tag{6.4}$$

Now the problem is as follows: find $u_l^{(k+1)}$ such that $f(\mathbf{u}^{(k+1)}, \mathbf{I}, q, t)$ is minimized where $\mathbf{u}^{(k+1)} = \left[u_1^{(k)}, u_2^{(k)}, \dots u_l^{(k+1)}, u_{l+1}^{(k+1)}, \dots u_N^{(k+1)}\right]$. The constraints (4.5) should be satisfied.

The search procedure may be repeated several times. In each step a different storage is selected by selecting one new outflow.

6.3 Control random search method

The minmax-type criterion (5.20) and representation of reservoir outflow described in Section 6.1 may cause non-convexity of the objective function. In such cases the global optimization search methods are needed. Procedures based on the Monte Carlo method, simulated annealing or others may be applied in the case presented. One global method, namely the Control Random Search, showed a good performance for deterministic models (Dysarz and Napiorkowski, 2002a), therefore we adjust this algorithm also for the stochastic case.

The original method was proposed by Price (1987). Its basis is a well known simplex method used in non-linear optimisation. The set of points from n-dimensional space is processed iteratively. At each step, new solution is generated by the reflection of a simplex vertex.

The algorithm starts from the creation of a set of points, greater than $n + 1$ points in n-dimensional space, selected randomly from the domain. The optimal number of points $10(n + 1)$ is taken as suggested by Price (1987). Let us denote the initial set as S. After evaluating the objective function for each of the points, the best x_L (i.e., that of the minimal value of the performance index) and the worst x_H (i.e., that of the maximal value of the performance index) points are determined and a simplex in n-space is formed with the best point x_L and n points (x_2, x_3, …, x_{n+1}) randomly chosen from S. Afterwards, the centroid x_G of points x_L, x_2, …, x_n is determined. The next trial point x_Q is calculated as the reflection of x_{n+1}, that is $x_Q = 2x_G - x_{n+1}$ (Niewiadomska-Szynkiewicz et al., 1996). If the last derived point x_Q is admissible and "better", it replaces the worst point x_H in the set S. Otherwise, a new simplex is formed randomly, and so on.

If the stop criterion is not satisfied, the next iteration is performed. This criterion may be formulated as

$$F_{ave} - F\left(x_L\right) < \varepsilon \tag{4.16}$$

where F_{ave} is the mean objective function value in the set, $F(x_L)$ the objective function value in the best point x_L and ε is the expected accuracy determined empirically (Dysarz and Napiórkowski, 2002a).

6.4 Numerical methods for partially differential equations

For our model the effective solution procedure for the flow transformation in the open channel is a problem of high importance. The models introduced in Section 4 are the sets of partially differential equations with initial and boundary conditions. The domain of the problem is set $D = \{(x, t): 0 \le x \le L, t \ge 0\} \subset R^2$. The solution of the problem consists of two functions of space and time: discharge $Q(x, t)$ and water depth $H(x, t)$. In general it is not possible to solve such a problem analytically. Numerical methods and special approximation schemes have to be used. There are three groups of such methods: the methods of characteristic, the finite difference method and the finite element method (including the finite volume schemes).

The choice of the method is restricted the same way as the choice of the model. The flow transformation part should provide as exact results as possible and the computations should not be too long. These two goals are conflicting and there is a need for a balance between them. The simplest and quickest schemes are finite differences schemes. Unfortunately they are not good in the case of full de Saint-Venant equations (4.7) - (4.8). Even the Preissman scheme recommended by many researchers (i.e., Mahmood and Yevjevich, 1975; Cunge et al., 1980) does not guarantee the success, though the stability of this method is well recognized. However, in many cases the application of such a complicated model is not necessary (Henderson, 1966), especially when we deal with uncertainty. The application of the simpler diffusive or kinematic wave model as a part of the stochastic control algorithm may provide results of similar quality. Application of simple finite differences schemes may be recommended for such cases, because this guarantees stability of numerical computations.

7. The single reservoir control problem - a simplified example

To illustrate the importance of explicit treatment of uncertainties in flood management a simplified example was tested. This is a single reservoir flood control problem. The system is shown in Figure 7.1. It consists of one reservoir with single inflow $I(t)$ and controlled outflow $u(t)$ and one end-user. The changes of reservoir storage $V(t)$ are described by mass balance equation

$$\frac{dV}{dt} = I - u \tag{7.1}$$

with initial condition $V(0) = V_0$. This equation was approximated by means of the Euler explicit method.

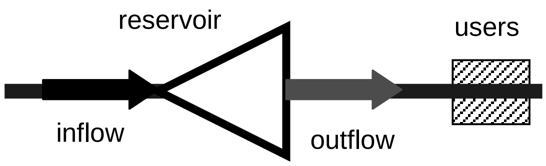

Figure 7.1 Single reservoir system

The first stage flood control rules are designed as so-called “basic rule”

$$u'[q,t_0](t) = \begin{cases} q & t \in [t_0, t_2] \\ I(t) & t \notin [t_0, t_2] \end{cases} \tag{7.2}$$

The main idea of this concept is as follows: At the beginning of the control horizon the reservoir outflow is equal to inflow. In time t_0 the reservoir starts performing with the equalized outflow q. The outflow from reservoir is equal to inflow once again in time t_2, which is determined as follows

$$t = t_1 \text{ or } t = t_2 \quad \text{when} \quad q = I(t) \quad \text{and} \quad t_1 < t_2 \,. \tag{7.3}$$

This control rule is shown in Figure 7.2. In this approach the reservoir may be emptied before flood comes, and the whole peak of the flow may be stored there. The second stage control rules $u''(t)$ are very simple, created as an if-then decision in order to satisfy the reservoir storage constraints

$$V_{\min} \le V \le V_{\max} \,. \tag{7.4}$$

This follows from the specifics of the second-stage optimization problem. When the reservoir storage exceeds the lower $V_{\min}$ or the upper $V_{\max}$ bound, the outflow from reservoir is corrected in such a way that it is equal to inflow $I(t)$.

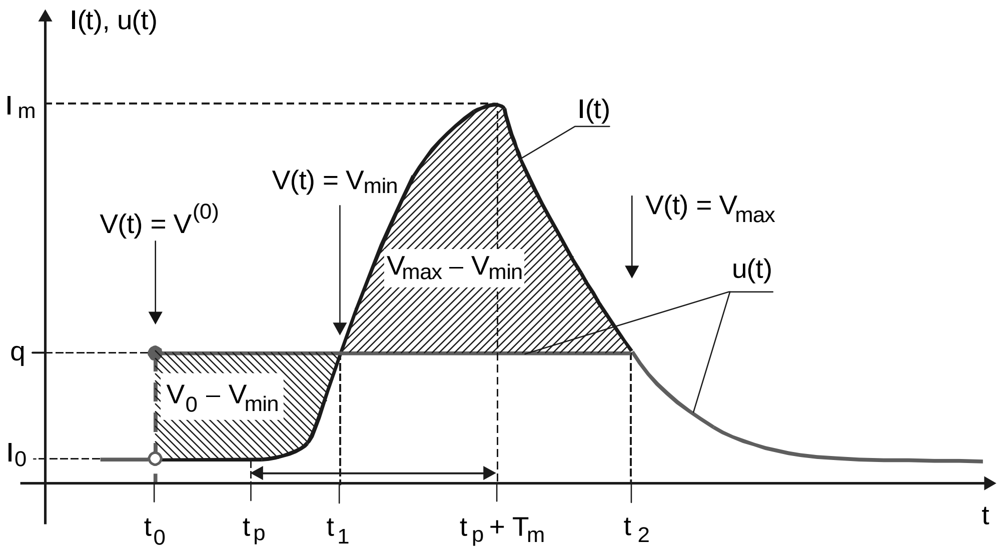

Figure 7.2 Basic rule control function and single maximum inflow

To simplify the problem an inflow with only one maximum peak was tested. One of many analytical formulas describing such an inflow is shown below

$$I(t) = \begin{cases} I_0 & t \le t_P \\ I_0 + I_m \left(\frac{t - t_P}{T_m} \right)^2 \exp\left[1 - \left(\frac{t - t_P}{T_m} \right)^2 \right] & t > t_P \end{cases} \tag{7.5}$$

where parameters I_0 and I_m are the basis flow and the maximum flow, respectively. t_P is the time of flood occurrence and T_m is the time of maximum flow occurrence after the beginning of the flood. The idea of such a representation of the inflow is shown in Figure 7.2.

It is assumed that the basis flow I_0 and the time when flood begins t_P are certain and known. For the tests their values were chosen as 10 m^3/s and 0 h, respectively. The forecasted values of maximum flow I_m and its time T_m are 600 m^3/s and 20 h, respectively, in the 48 h control horizon. It is assumed that these values' validity is 70 % and they have multivariate normal distribution.

In this simple task the chosen risk indicator is a minmax-type criterion

$$\min_{q,t_0} E_{(\mathbf{I},q)} \left\{ \max_{t \in [0,T_H]} \mathbf{u}'[q,t_0](t) + \beta_2 \int_0^{T_H} [u_j''(t)]^2 \, dt \right\} \tag{7.6}$$

There is no need to add the second part of the (4.17) objective function. The demand of water storing at the end of the time horizon is satisfied by optimal control rules. The control random search method described in section 6 was used to solve the problem.

Table 7.1

Single reservoir control problem - results obtained

	deterministic case	stochastic case
optimal maximum outflow	83.5 m^3/s	101.9 m^3/s
probability that assumed level is not exceeded		
max u ≤ 83.5 m^3/s	61 %	–
max u ≤ 101.9 m^3/s	64 %	78 %

The deterministic and stochastic cases were compared. In the first case the controls were selected only on the basis of deterministic inflow forecast. In the stochastic case a wide range (scenarios) of possible inflows was considered. Although the optimal maximum outflow is lower in the deterministic case (see Table 7.1), the probability that the assumed critical level is not exceeded for a wide range of possible inflows is much better in the stochastic approach. We can observe a significant difference even in such a simple application with the normal density function. Careful consideration of real inflow conditions can make this conclusion much stronger.

8. Concluding remarks

In the research presented the problem of a reservoir flood defense system control under uncertain inflows was studied. The problem is common for many countries. In Poland the biggest flood event in 1997 caused losses equal to 2.9 % of the GDP. The case study system chosen in this paper, the Nysa Klodzka basin, is almost in the center of the “flood strike”. The flood defense system in this region consists of two big reservoirs in series located on the Nysa Klodzka. Since the reservoirs affect the flow conditions in the Odra river, the safety of many big Polish cities and factories depends on the proper selection of their controls. The linkage between the design of reservoirs and their controls is critically important for the effectiveness of the flood defense system, as was shown in Section 2 by using the example of flood wave interaction in the junction of the Odra and Nysa Klodzka rivers affected by severe flooding in 1997.

The existing decision support system for flood control consists of methods and algorithms which can be classified as parts of the inflow forecast module and control algorithms. that enable explicit treatment of uncertainty of the inflow forecast.

The mathematical description of the system is based on physical principles: mass and momentum balances. The nonlinearity may be involved in modeling of two processes: flow routing in open channels and reservoir mass balance. The importance of reservoir storage constraints is critical. Their violation results in the destruction of the system, which causes high losses. For dealing with uncertainties a stochastic two-stage recourse model is proposed, which treats jointly ex-ante and ex-post decisions. The complexity of the model causes several computational problems, which can be overcome by numerical techniques described in Section 6.

As was indicated in Section 7, we can observe a significant difference in the results between deterministic and stochastic approaches even in a very simple single reservoir case. The real situation is much more complicated and the stochastic approach to the problem discussed may be critically important for effective flood management, since it allows to find robust controls against flooding by taking into account a set of possible scenarios in contrast to only one scenario of the deterministic models.

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