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Control of the Reservoirs System During Flood: Concept of Learning in Multi-Stage Decision Process

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Control of the reservoirs system during flood: Concept of learning in multi-stage decision process

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Contents

Abstract

Although floods are not the strongest or the most sudden physical phenomena in the world, they appear to be the one of the most disastrous events. During the last few decades we have observed an unusual frequency of flood events. 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. It could be said that floods have become one of the main development barriers for countries which are unable to cope with this problem.

In the presence of extreme floods proper water management strategies have become dramatically important. Flood protection in the catchment scale requires application of efficient decision support system. However, the uncertainty linked to the unknown inflows scenarios makes this problem extremely difficult. In the report the possible structure of a decision support tool is presented. The elements of the system are discussed and some examples from the Nysa Klodzka reservoirs system are given

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About the Author

In 2003 Dr. Tomasz Dysarz from the Institute of Geophysics Polish Academy of Sciences participated in the Young Scientists Summer Program of the International Institute for Applied Systems Analysis in Laxenburg, Austria. His final report was awarded the Mikhalevich Scholarship which enabled him to continue his research at the Institute in 2004. The report presents the result of his research in the period June-August 2004. Since October 2004 Dr. Tomasz Dysarz is working at the Department of Hydraulic, Agricultural University of Poznan, Poland.

Control of the reservoirs system during flood;

Concept of learning in multi-stage decision process

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1. Introduction

During last decades we have observed an unusual increase of losses caused by extreme rainfalls and floods. Ashton et al. (2003) reported that flood damages in the period 1989-98 were ten times greater than losses caused by the high water level in the decade between 1960-69. According to the mentioned report flood losses increase from decade to decade. The indicated explanations are twofold. The increase of human population and economic growth cause increase of investments density in economically attractive but flood prone areas. Economic growth and development of industry lead to local and global climate changes resulting in an increased frequency of extreme meteorological and hydrological events such as floods and droughts. These kinds of phenomena were observed in Europe during the last decade. In 1997 many cities in Poland, Czech Republic and Slovakia were struck by intensive rainfalls and river flooding. A few years later the horror came back. In 2002 extreme floods occurred in Germany and once again in the Czech Republic and Slovakia. Not only European cities suffer from floods. The problem occurs also in other parts of the world, for example in China, United States, Southern Africa and many others.

As a response to the increasing danger caused by weakly controllable and unpredictable hydrological events, serious economic and political organizations founded scientific projects to deal with these problems. The European Commission started to support scientific projects aimed at flood risk mitigation or early flood warning systems. In the Fifth Framework Programme there were 100 projects dealing with meteo- and hydrology topics focused on flood hazards (Ashton et al., 2003). The considered analysis led to management strategies classified familiarly as “hard” and “soft” (Menzel and Kundzewicz, 2003). The first group contains development of flood protection infrastructure as dams, reservoirs, dikes and polders. In the second group there are the management strategies made on the basis of existing infrastructure. This means actions taken in operational conditions in order to decrease flood risk and losses. These methods include forecasting, warning and control of dams and polders.

This report presents the problem of reservoir system control in flood conditions which should be classified as “soft” strategies. The controllable structures deal with middle and short term strategies drawn on the basis of the current state of the system. Various operational decision rules were analyzed recently, i.e., by Agthe et al. (2000), Takeuchi (2002), Shim et al. (2002), Islam and Sado (2002) and many others. However, the main problem with the implementation of such strategies is still linked with computational time requirements (Valdes and Marco, 1995). The designed algorithms are very time consuming which makes them useless in operational conditions.

The main purpose of establishing artificial reservoirs and dams is to control the water discharge variability and uncertainty. The storage of reservoirs should significantly affect flow conditions in the streams located down the reservoirs releases. Such engineering structures are built to supply water, produce hydropower or prevent from floods . Other reservoirs purposes are the inland navigation and tourism. Although the influence of the reservoirs on the water use conditions improvement is beyond any doubt, some new problems linked with reservoir performance arise. For long term use of the reservoir the most important processes are linked with the break in transport processes continuity. The sediment and pollutants transported with the water accumulate in the reservoir. In effect the effective reservoir’s capacity is decreased. What is worse, water intake facilities may be destroyed. Water quality in the reservoir becomes worse from year to year. On the other hand the water released from the reservoir is free of dissolved pollutants and sediment materials. In addition the water stream has huge mechanic energy. This energy is used to fill the stream with sediment up to the previous river sediment load. The material is taken from the river bed down the dam what causes sequential erosion of the ground and may in turn cause the collapse of the dam.

Although the long term problems linked to reservoir performance are very significant there are many ways to prevent unwanted events. The risk is larger in operational conditions especially during high water levels and floods. The flow conditions below the dam are more predictable and stable than before the reservoir was built. Hence, the decision maker problem is to select such releases from the reservoir or reservoirs that the flood losses below the system are minimized. In many cases the mitigation of flood losses may be considered as minimization of water level in chosen points of the river system. So, for these points the control criterion may be specified as

$$\min \max_{t \in [t_0, t_0 + T_H]} H_r , \tag{1}$$

where H_r is the water level, t_0 is the decision time and T_H is the control horizon. Although the relationship between discharge and water level in unsteady flow is not unique, for the sake of simplicity in many cases the above criterion is replaced by the minimization of peak water discharges Q_r

$$\min \max_{t \in [t_0, t_0 + T_H]} Q_r . \tag{2}$$

The decision maker has to select proper releases from the reservoirs matching criterion (1) or (2). It is not an easy task in big catchments where the river lateral inflows play a significant role in forming the flow conditions. In some cases, for example in the Nysa Klodzka catchment, there are at least two flow peaks running different channels in the system (Dysarz, 2003). Only one of them may be controlled. The problem is to control the reservoir located in one tributary in such a way that flow peaks in the junction of two rivers are shifted. Then the flow peak below the junction is decreased. In this way the flood losses are minimized.

The optimal decision should reduce flow peak and store the flood wave by proper use of the reservoir capacity. In the case of a big flood the use of the whole admissible capacity is necessary. At the end of a flood the reservoirs should be full of water. This would be the ideal situation. In reality the conditions above the reservoir are uncertain. The future inflows to the reservoir are not known and the whole risk is put into decision maker consideration. The inflows may be predicted but up to now the accuracy of such predictions is low. This uncertainty causes new danger. If the releases from the reservoir are too low, the maximum admissible capacity may be exceeded and the dam may be broken by overtopping. Such events cause much higher losses than floods themselves. Hence, wrong decisions may lead to bigger damages than no prevention from floods. Due to the forecasting errors the danger of dams overtopping is really serious. The information about the state of the reservoir collected in the dam is much more certain. This is the reason why in many cases the decision-makers relay on rule curves during extreme events (Valdes and Marco, 1995). Hence, no future forecasts are used. It means that the reservoir protects itself only in the current moment without any link to large scale situation in present and future.

This seems not to be good practice. Experiences of historical floods show that such strategy may lead to flood wave interaction and huge flood damages. The example from the Nysa Klodzka catchment in southern part of Poland was given by Dysarz (2003). The goal of this paper is to present the concept of flood damages reduction in real-time conditions on the basis of middle- and short-term forecasts even if the predictions are not perfect. The key problem is adaptation of the system to changing inflows conditions in presence of new available information about the future. The real decisions should be made on the basis of short-term (24 – 48 h) forecasts which are more accurate. However, some options should be open due to the middle-term (up to 10 days) considerations. As the results of the last European Commission projects show, such information may be provided in operational conditions.

The main goal of the presented report is to introduce the concept of uncertainty decreasing in flood protecting reservoirs management. The main basis of the concept is separation of long-term (or rather middle-term) analysis and short-term implementation of particular decisions. Such an approach was chosen to guarantee decisions flexibility in the presence of changing flow conditions and new available observations. The considerations and conclusions in this report are presented in the following chapters. First the equations describing the dynamic of reservoirs system are shown. In the next chapter the problem of inflow forecast is discussed. The main idea of the proposed procedure is shortly introduced in the fourth chapter. The fifth chapter consists of detailed problem formulation. Then the complexity of the problem is discussed and some detailed solutions are proposed including: design of the proper control rules, decomposition of the problem and selected approaches to minimax optimization. The concluding remarks are presented in the last chapter.

2. Reservoirs system

In general the reservoirs system may be modeled as a network of storages, channels and inflow points. The main focus is the safety or water demand in some points or some areas of the system. The basic types of the system are reservoirs in series and reservoirs in parallel shown in fig. 1 and 2. Although the mixed systems, as for example shown in fig. 3, are very common, the main considerations may be limited to the basic cases. Extending the main ideas for the mixed systems should be easy.

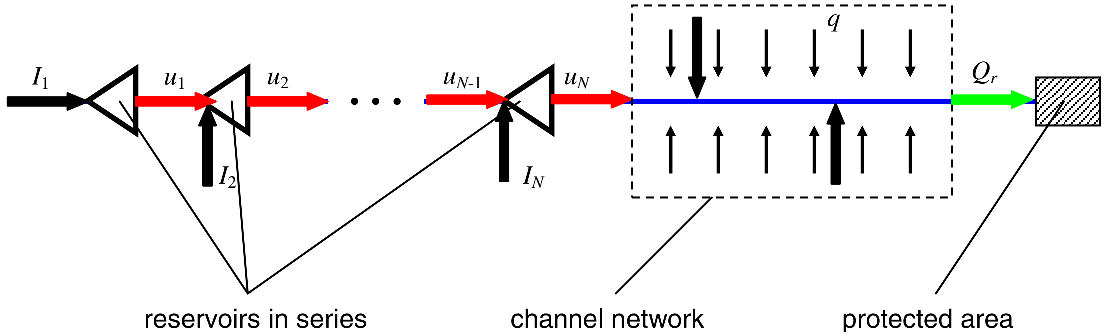

Fig. 1. The system of reservoirs in series – schematic view

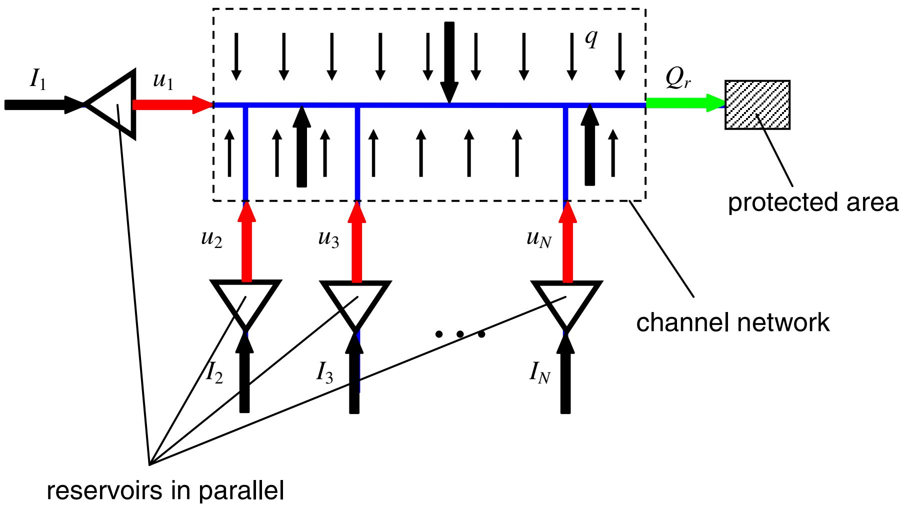

Fig. 2. The system consisting of reservoirs in parallel – schematic view

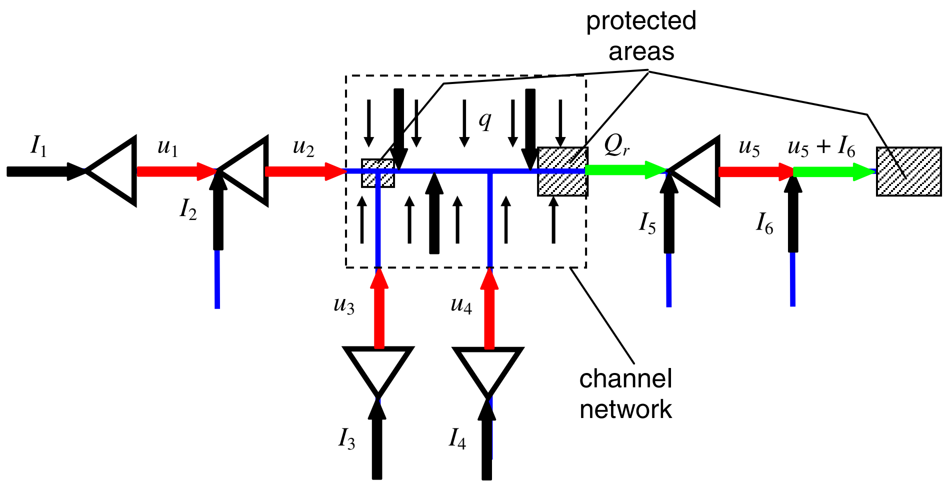

Fig. 3 Example of mixed system

Assuming that the channels connecting reservoirs in the system are short enough to neglect the transformation of flow, the system of reservoirs in series or in parallel may be described by the linear ordinary differential equations of the form

$$\frac{d\mathbf{V}}{dt} = \mathbf{EI} + \mathbf{Bu}, \tag{3}$$

where $\mathbf{V} = [V_1, V_2, \ldots, V_N]^{\mathrm{T}}$ are the reservoirs storages (N – number of reservoirs in the system), $\mathbf{I} = [I_1, I_2, \ldots, I_N]^{\mathrm{T}}$ are the inflows to the reservoirs, $\mathbf{u} = [u_1, u_2, \ldots, u_N]^{\mathrm{T}}$ are the controlled reservoirs outflows. $\mathbf{E}$ is the unit-matrix and $\mathbf{B}$ is the matrix of coefficients of the size $N \times N$. For the system of reservoirs in series $\mathbf{B}$ has the following form

$$\mathbf{B} = \begin{bmatrix} -1 & & & & & \\ 1 & -1 & & & & \\ & \ddots & \ddots & & & \\ & & 1 & -1 & & \\ & & & \ddots & \ddots & \\ & & & & 1 & -1 \end{bmatrix} \tag{4}$$

In the system of the reservoirs in parallel $\mathbf{B} = -\,\mathbf{E}$. The set of differential equations is completed with the initial condition $\mathbf{V}(t = 0) = \mathbf{V}_0$. The constraints describing the admissible releases and storages are imposed on the performance of the system

$$\mathbf{U}_{\min} \le \mathbf{u} \le \mathbf{U}_{\max} \qquad \mathbf{V}_{\min} \le \mathbf{V} \le \mathbf{V}_{\max} \tag{5}$$

The outflow from the system Q_r is formed by the reservoirs releases **u** and spatially distributed inflow q which may be only measured or predicted. The model of the system outflow may be shown as

$$Q_r = \psi(\mathbf{u}, q), \tag{6}$$

assuming that system boundary is properly defined. The later statement means that the flow conditions in the outlet of the system do not influence the flow conditions in the system. If the criterion (1) is taken into account the model of (6) is replaced by equivalent one

$$H_r = \Psi(\mathbf{u}, q) \tag{7}$$

expressing the relationship between reservoir outflows **u**, uncontrollable inflows q and water levels H_r in the outlet of the system.

The water levels $\mathbf{h} = [h_1, h_2, \ldots, h_N]^{\mathrm{T}}$ in the reservoir may be measured almost continuously. The area covered by water $F_i(h_i)$ ($i = 1, 2, \ldots, N$) for the certain water level h_i is one of the reservoir geometrical characteristics. For engineering purposes it is considered as a curve expressing the relationship between F_i and h_i. The change of reservoir storage dV_i may be written as

$$dV_i = F_i(h_i)\, dh_i. \tag{8}$$

Hence, the linear system of ordinary differential equations (3) may be presented in nonlinear form

$$\frac{d\mathbf{h}}{dt} = \mathbf{f}(\mathbf{h})^{\mathrm{T}}(\mathbf{EI} + \mathbf{Bu}), \tag{9}$$

where $\mathbf{f}(\mathbf{h})$ is a vector of the form $[F_1^{-1}(h_1), F_2^{-1}(h_2), \ldots, F_N^{-1}(h_N)]^{\mathrm{T}}$. The formulae (9) is useful if the attention is mainly focused on handling of release facilities. The outflow from the reservoir depends on the water level in the reservoir and the set of parameters $\mathbf{z}_i = [z_{i1}, z_{i2}, \ldots]$ ($i = 1, 2, \ldots, N$) describing the outflow gates opening

$$u_i = \varphi(h_i, \mathbf{z}_i). \tag{10}$$

In such case also the upper constraints on the reservoir outflows should be considered as dependent on water levels in the reservoir

$$\mathbf{U}_{\min} \le \mathbf{u} \le \mathbf{U}_{\max}(\mathbf{h}). \tag{11}$$

The future inflows to the system $\mathbf{I}(t)$ and $q(x, t)$ are not known and may be only predicted with some finite accuracy. However, the statistics of inflow prediction validity may be defined on the basis of historical flood events. Hence, the behavior of the system is considered stochastic.

3. Admissible inflows forecasts

To achieve the above specified goals decision support systems including monitoring, predicting, modeling and control procedures should be used. The elements of the decision support system may be classified in two groups: forecasting and optimization techniques. Both of them include several modeling techniques enabling determination of a system response as discharges and/or water levels in specified points of the considered area. The problem of inflow forecasting is not the area of the presented research but a short overview would be useful for clear understanding of the discussed problem of the control of reservoirs in uncertain inflow conditions. The inflow prediction module consists of two main parts: precipitation forecast and rainfall – runoff transformation model. These parts form meteorological and hydrological forecasts.

The precipitation forecast is based on the so called global circulation models (GCM) and downscaling techniques. GCMs are well known models describing the evolution of global weather variables 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 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 methods from the first group were recently investigated by many researchers, for example by Jones et al., (1995), Murphy (1999), Bates et al. (1998). The dynamic downscaling is based on the same kind of physical laws as global circulation models but resolution is much finer. In statistical downscaling relationships between large scale climate features and regional characteristics are used to produce local weather characteristics. The examples of such approach may be found in Burger (1996), Conway and Jones (1998), Sailor et al. (2000), Stehlik and Bardossy (2002), Wilby et al. (2002). A range of summary statistics that could be provided by 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) there are two basic types of rainfall – runoff models: kinematic wave approach and 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 and White (1977, 1978) and others. In the second group of runoff – rainfall 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).

As discussed by Dysarz (2003) inflow forecasting is very inaccurate. The main value of forecasting in the described way should be considered statistically. This means that the decision-maker obtains the information as something happened in shorter or longer future, the maximum flow during flooding may exceed specified value with given probability, and so on. Only short-term inflow predictions, 0-3 days, were seriously taken into account in reservoir management. This period is to short to control huge spatially spread reservoirs systems.

A significant step forward was done in some scientific projects sponsored in the European Fifth Framework Programme. Some results will be discussed here to illustrate the background for the operational control of reservoirs during flood. Very interesting example is the EFFS project aiming at developing the European Flood Forecasting System. The useful results obtained in this research include data on control of reservoirs during flood. The results were presented in project reports and some publications. The short discussion presented below is based on a project final report (*An European Flood Forecasting System EFFS*, 2003) and summary of this project given by De Roo et al. (2003).

The main project goal was to develop a European-scale flood early warning system. The main system part is forecasts module for 4-10 days in advance. Several numerical models were used in the EFFS project. The precipitation forecasts are calculated by means of global and local Numerical Weather Prediction models. Water balance models were used for the catchment hydrology modeling. The LISFLOOD model was implemented as the flood simulation model. High-resolution flood inundation models enable the identification of flooded areas. The modeling framework was applied in five study areas located in Europe. These are Meuse (France, Belgium, the Netherlands), Odra (Czech Republic, Poland, Germany), Po (Italy), Mures (Romania), Sava (Danube, Slovenia). For each study area the forecasts were formulated by simulation of historical disastrous flood events. As an example the results for the Odra catchment are presented below (fig. 4). The flood event in 1997 was simulated. In the figures there are several flow forecasts scenarios (black, green and red lines) specified in subsequent days for the Miedonia gauge station. The scenarios are compared with the real flows (blue line). The accuracy of the flow peak forecasting increases if the time between the forecast specification and peak occurrence is shorter. However, even the very early predictions may be useful. The forecasts indicate that "something happens". Such warnings should be the beginning of the prevention actions.

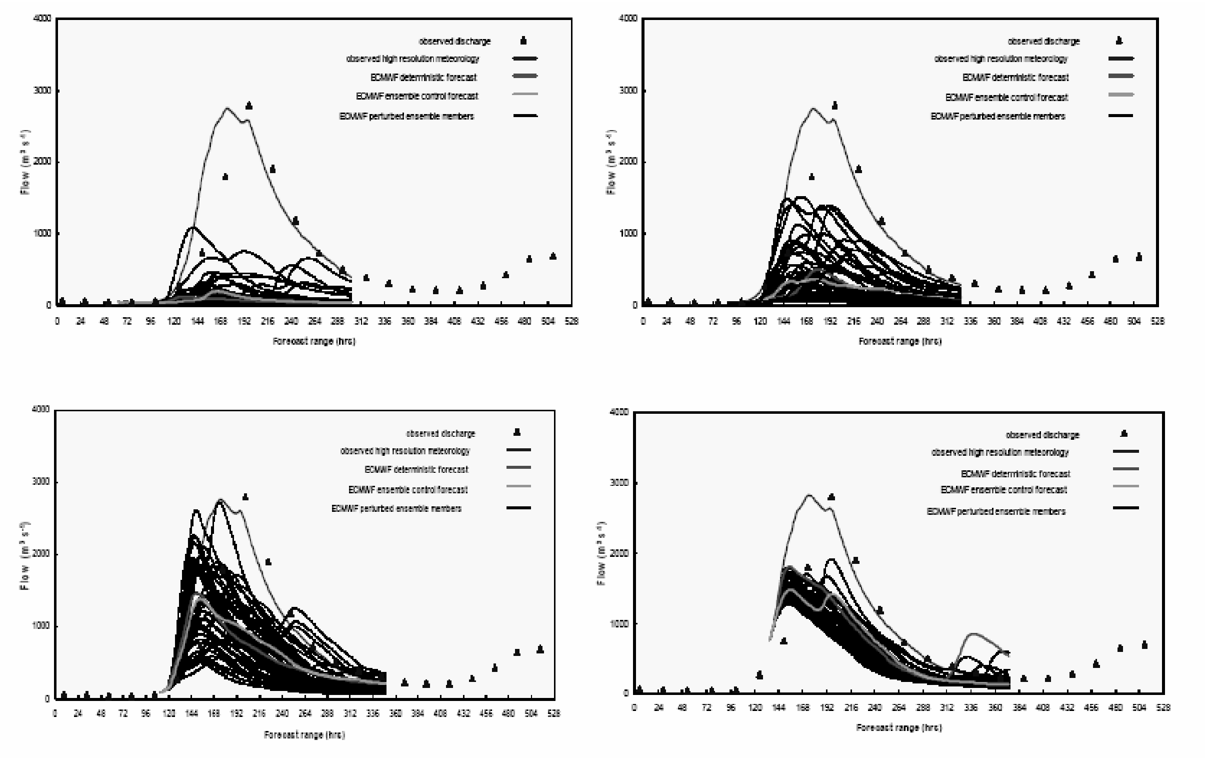

Fig. 4 Flow forecast scenarios formulated for the Miedonia gauge station in Odra catchment for the flood event simulation in 1997; The results are from the EFFS project final report "*An European Flood Forecasting System EFFS*" (2003)

It seems to be possible to specify a number of inflow scenarios before the flood is coming as well as to monitor and predict the future changes during the event. The next problem is what the decision-makers may do with such information. The inflow scenarios should be used with different decisions selected from the admissible set. In the presented case the decisions mean different reservoirs releases scenarios. The behavior of the system influenced by inflow conditions and taken decisions may be simulated and the results may be assessed. This evaluation should lead to which decision is the best in the statistical sense. However, the decisions may be changed during the flood event according to the changes of our expectations about the future inflow conditions. Hence, the parameters of system performance should be selected in such a way that the flexibility of the system is still preserved. Due to the high complexity of the problem the decomposition schemes and optimization methods are very useful. The algorithm which should satisfy the described requirements is presented in the next section.

4. *Main idea of adaptive multi-stage algorithm*

As it was mentioned in the previous section the reservoir control problem should be considered as a stochastic optimization task due to the inflow uncertainty. In general such a problem is formulated as follows (Ermoliev & Wets, 1988b): find set of control variables $\mathbf{u} \in U \subset R^m$ such that the constraints

$$g_i\left(\mathbf{u},\boldsymbol{\omega}\right) \leq 0 \qquad \text{for } i = 1, 2, \ldots n \tag{12}$$

are satisfied and the objective function

$$z = f_0\left(\mathbf{u},\boldsymbol{\omega}\right) \tag{13}$$

is minimized in some sense for each $\boldsymbol{\omega} \in \Omega \subset R^q$ assuming $\boldsymbol{\omega}$ is known. In the above formulae $\mathbf{u}$ is vector of control variables and $\boldsymbol{\omega}$ is unknown vector of random variables. In the considered reservoir control problem the inflows to the system are random variables. Set Ω consists of probable $\boldsymbol{\omega}$ elements. This set with 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.

The minimax dynamic optimization problem may be written in the same manner: find control functions $\mathbf{u}(t) \in U \subset R^m$ such that the state equations

$$\frac{d\mathbf{x}}{dt} = \mathbf{f}\left(\mathbf{x}, \mathbf{u}, \boldsymbol{\omega}, t\right) \qquad \mathbf{x}(t_0) = \mathbf{x}_0 \tag{14}$$

and constraints

$$g_i\left(\mathbf{u}, \mathbf{x}, \boldsymbol{\omega}, t\right) \le 0 \qquad \text{for } i = 1, 2, \dots n \tag{15}$$

are satisfied and the objective function

$$z\left(\mathbf{u}, \boldsymbol{\omega}\right) = h\left(\mathbf{x}_H\right) + \max_{t \in [t_k, t_k + T_H]} J\left(\mathbf{u}, \mathbf{x}, \boldsymbol{\omega}, t\right) \tag{16}$$

is minimized in some sense for each $\boldsymbol{\omega} \in \Omega \subset R^q$. In the above formulae $[t_k, t_k + T_H]$ is control horizon, $\mathbf{x}(t) \in X \subset R^p$ is state vector, $h(\mathbf{x}_H)$ is a function determined for the final system state $\mathbf{x}_H = \mathbf{x}(t_0 + T_H)$ and $J(\mathbf{u}, \mathbf{x}, \boldsymbol{\omega}, t)$ is the control criterion element for which the maximum value is to be minimized. Such problem arises when the decision **u** forming future states of the system **x** has to be made on the basis of imperfect forecasts of $\boldsymbol{\omega}$ values. Constraints (12) and (15), state equations (14) as well as the objective function (13) or (16) depend on random $\boldsymbol{\omega}$ variables. Hence, constraints may not be satisfied for some $\boldsymbol{\omega}$ in the set Ω. The same is with an objective function which cannot be minimized for all $\boldsymbol{\omega}$, therefore, proper probabilistic definition of (12)-(16) is needed.

For the next considerations the attention is focused on the dynamic case. To formulate the problem precisely (14) – (16) one has to consider a wide range of exact statements of the above problem according to specifying in which sense function (16) is minimized and constraints (15) with state variables (14) are satisfied. On this basis appropriate criterion and constraints should be formulated. The approaches to the problem may be classified in several groups. The most common are (Ermoliev & Wets, 1988b):

- scenario approach;
- reliability approach;
- averaging of objective function, constraints and state equations;

However, in each of the above approaches the constraints may be violated. This problem is of the great concern in reservoir management. Violation of constraints means dam overtopping resulting in dam break. As it was indicated in the introduction this is the main risk with using reservoirs and dams as flood protecting structures. Hence, straightforward strategic planning approach as mentioned above should be replaced by the procedure based on sequential monitoring and control. An important element is also incorporating long- or rather middle-term information into operational management during flood. Due to these requirements the application of two approaches may be considered:

- adaptive two- or multi-stage approach or
- adaptive trajectory planning.

They both are similar. Their main features are considerable flexibility and adaptation in changing environment conditions. These overcome the problem of constraints violation. The first approach is the stochastic optimization model with ex-ante (forward looking) optimization and adaptive recourse actions (see Ermoliev and Wets (1988b)). The main assumption is that the control variables $\mathbf{u}$ are replaced by control actions taken in advance $\mathbf{u}'$ and adaptive recourse actions $\mathbf{u}''$ as

$$\mathbf{u} = \rho(\mathbf{u}', \mathbf{u}''). \tag{17}$$

The first control rules are determined before observation of random variables $\boldsymbol{\omega}$ from Ω. They are selected at the beginning of the decision process, where the information about the environment is limited. The later controls are selected for the specified $\mathbf{u}'$ and particular observed or better predicted environment conditions $\boldsymbol{\omega}$. These actions are determined during the control process when the decision-maker has some information (measurements) describing $\boldsymbol{\omega}$ at his/her disposal.

For the system which dynamic is described by state equations of the form (14) the problem may be formulated in a similar way. Assuming that control variables $\mathbf{u}$ are represented by relationship (17) in the first level the decision-maker has to find such $\mathbf{u}' \in U'$ that the objective function

$$z_1(\mathbf{u}') = E_{\boldsymbol{\omega}}\left\{ g_0(\mathbf{u}', \boldsymbol{\omega}) + q(\mathbf{u}', \boldsymbol{\omega})\right\} \tag{18}$$

is minimized. The averaging operator $E_{\boldsymbol{\omega}}$ is defined for any random function $\varphi(\,.\,, \boldsymbol{\omega})$ as

$$E_{\boldsymbol{\omega}}[\varphi(\,.\,,\boldsymbol{\omega})] = \int_{\Omega} \varphi(\,.\,,\boldsymbol{\omega}) P(\mathbf{d}\boldsymbol{\omega})\,. \tag{19}$$

In this case $g_0(\mathbf{u}', \boldsymbol{\omega})$ is the optimal solution of the problem: for given $\mathbf{u}'$ and particular sample $\boldsymbol{\omega} \in \Omega \subset R^q$ find $\mathbf{u}'' \in U''$ such that state equations

$$\frac{d\mathbf{x}}{dt} = \mathbf{f}\left(\mathbf{x}, \rho\left(\mathbf{u}', \mathbf{u}''\right), \boldsymbol{\omega}, t\right) \qquad \mathbf{x}(t_0) = \mathbf{x}_0 \tag{20}$$

with constraints

$$g_i\left(\rho\left(\mathbf{u}', \mathbf{u}''\right), \mathbf{x}, \boldsymbol{\omega}, t\right) \le 0 \qquad \text{for } i = 1, 2, \ldots n \tag{21}$$

are satisfied and the objective function

$$z_2\left(\rho\left(\mathbf{u}', \mathbf{u}''\right), \boldsymbol{\omega}\right) = h\left(\mathbf{x}_H\right) + \max_{t \in [t_k, t_k + T_H]} J\left(\rho\left(\mathbf{u}', \mathbf{u}''\right), \mathbf{x}, \boldsymbol{\omega}, t\right) \tag{22}$$

is minimized. So $g_0(\mathbf{u}', \boldsymbol{\omega})$ is

$$g_0\left(\mathbf{u}', \boldsymbol{\omega}\right) = \min_{\mathbf{u}''} z_2\left(\rho\left(\mathbf{u}', \mathbf{u}''\right), \boldsymbol{\omega}\right) \tag{23}$$

In (18) function $q(\mathbf{u}', \boldsymbol{\omega})$ describes the aggregated cost of recourse action.

The second approach namely adaptive trajectory planning may be presented as follows: find such state trajectory $\mathbf{x}(t) \in X \subset R^p$ that objective function

$$E_{\boldsymbol{\omega}}\left\{h\left(\mathbf{x}_H\right) + \max_{t \in [t_k, t_k + T_H]} J\left(\mathbf{u}, \mathbf{x}, \boldsymbol{\omega}, t\right)\right\} \tag{24}$$

is minimized and the constraints (15) are satisfied. In (24) control variables $\mathbf{u}$ are determined as the solution of state equations (14) for particular $\boldsymbol{\omega}$ and selected state trajectory $\mathbf{x}$.

Both approaches may be used as a preliminary control in selecting the desired behavior of the system in long- or middle-term horizon. The information obtained as the solution of the presented problems should be incorporated into operational research and sequentially updated as soon as new information about $\boldsymbol{\omega}$ is available. This concept is described in the next section for the particular problem namely control of reservoir systems during flood.

5. *Problem formulation*

As it was discussed in the previous section the inflow forecasts may be appropriately accurate only in a short time horizon, about $T_F = 48 – 72$ hours. At any decision making moment t_k, the proper outflow from the reservoirs should be selected for the nearest period of time $[t_k, t_k + T_F]$. In this case "outflow" means the vector valued function of one real argument $\mathbf{u}(t)$ or rather the set of parameters α_1, α_2, … describing this function. The important thing is that the decision-maker has to select real "values" fitting uncertain future conditions. For a short time horizon T_F the danger of uncertainty may not be dramatic. However, floods are the phenomena of longer duration. What a decision-maker should avoid is filling up reservoirs before the flow peak comes or releasing water from reservoirs in such a moment that flood waves interact in channels. The flood wave movement and reservoir performance should be analyzed in longer time horizon $[t_k, t_k + T_H]$, where T_H may be up to 10 – 11 days. Hence, the operational reservoir management should take into account possible long term conditions in the system.

Considering the current inflow forecasting opportunities the use of adaptive and flexible monitoring-and-control algorithms seems to be the proper choice. In this section the attention will be focused on the control part of such a procedure. The decision-making process is divided into two main parts: upper and lower. In the upper part all possible inflow scenarios for the period $[t_k, t_k + T_H]$ are analyzed and then proper reservoir storages $\mathbf{V}_F$ in the end of forecasting time horizon $t_k + T_F$ are determined. To do this the simplified behavior of the decision-maker in real time conditions should be simulated. Such an approach is consistent with the Bellman optimality principle which states that *from any point on an optimal trajectory, the remaining trajectory is optimal for the corresponding problem initiated at that point*. At the upper level of the algorithm such a point of trajectory $(t_0 + T_F, \mathbf{V}_F)$ should be selected that in time $t_0 + T_F$ the decision-maker is not limited by the earlier decisions. The options are still open at the time $t_0 + T_F$ and may be selected depending on the changing inflow conditions.

At the lower level the attention is focused on the short time horizon $[t_k, t_k + T_F]$. The reservoirs storages $\mathbf{V}_F$ are the necessary boundary for the selected decisions. The maximum outflow from the system Q_r has to be minimized in this period of time but the storages of the reservoirs at the end $t_k + T_F$ have to be kept in the level $\mathbf{V}_F$ determined previously. For this purpose some assumptions about the future inflows ($\mathbf{I}$, q) have to be taken namely one inflows scenario should be selected. However, these assumptions may be wrong and should be checked during the period $[t_k, t_k + T_F]$. Hence, the forecasting horizon may be divided into smaller periods of time $\Delta\tau$ such that $M = T_F / \Delta\tau$. During each period of time $t = t_k + i\,\Delta\tau$ ($i = 1, 2, \ldots, M - 1$) the decision-maker checks the reservoirs storages and water levels in the channels. The real inflows to the system in the past period $\Delta\tau$ may be determined on this basis. Then the assumptions about inflows are verified and the controls for $[t_k + i\,\Delta\tau, T_F]$ are updated.

Due to the inflows uncertainty and danger of dam break by overtopping some additional restrictions on the selection of reservoirs outflows $\mathbf{u}$ have to be imposed. The selected controls should not allow overtopping before the next checking time even if the assumptions about inflows are wrong. If the number of scenarios was taken into account in the upper level control, the storages probability distributions may be determined for each control selected in the period $[t_k + i\,\Delta\tau, T_F]$ and for the nearest checking time $t_k + (i + 1)\,\Delta\tau$. If the real storages of the reservoir differ from decision-maker expectations significantly, it means that improper scenarios were analyzed in the upper level. The requirement for running once again the upper level procedure should be sent.

In the below subsections the upper and lower control models are formulated. The problem of information exchange between these models is also shortly discussed.

5.1 Upper level control: design of bounds for operational control

In time t_k the reservoirs storages $\mathbf{V}_k$ are known and the desired storages $\mathbf{V}_H$ in time $t_k + T_H$ related to other reservoirs purposes may be determined. It is also assumed that in time t_k the set of future inflows scenarios $(\mathbf{I}, q)^{(l)}$ ($l = 1, 2, \ldots$) for the next period of duration T_H is defined. The inflows forecasts are formulated on the basis of the current hydro-meteorological situation in the basin. The information obtained from historical data records may also be incorporated in the formulation of inflows scenarios. The forecast may be updated in time $t_k + T_F$. The control problem formulated in time t_k is as follows: for a given $\mathbf{V}_k$, $\mathbf{V}_H$ and a set of possible inflows scenarios $(\mathbf{I}, q)^{(l)}$, $l = 1, 2, \ldots$ find such $\mathbf{V}_F$ that the constraints

$$\mathbf{V}_{\min} \leq \mathbf{V}_F \leq \mathbf{V}_{\max} \tag{25}$$

are satisfied and objective function

$$z_{10}\left(\mathbf{V}_F\right)=E_{(\mathbf{I},q)}\left\{z_{11}\left(\mathbf{V}_F,\mathbf{I},q,\mathbf{u}\right)\right\} \tag{26}$$

is minimized. The outflows from the reservoirs **u** and function z_{11} are determined as the solution of the problem: for a given $\mathbf{V}_k$, $\mathbf{V}_H$ and $\mathbf{V}_F$ and particular inflows scenario ($\mathbf{I}$, q) find such outflows **u** that the state equations

$$\frac{d\mathbf{V}}{dt}=\mathbf{EI}+\mathbf{Bu}\,, \tag{27}$$

$$Q_r=\psi\left(\mathbf{u},q\right), \tag{28}$$

with initial condition $\mathbf{V}(t_k) = \mathbf{V}_k$, and constraints

$$\mathbf{U}_{\min} \le \mathbf{u} \le \mathbf{U}_{\max}, \qquad \mathbf{V}_{\min} \le \mathbf{V} \le \mathbf{V}_{\max}, \tag{29}$$

$$\mathbf{V}(t_k + T_F) = \mathbf{V}_F, \qquad \mathbf{V}(t_k + T_H) = \mathbf{V}_H, \tag{30}$$

are satisfied and the objective function

$$z_{11}\left(\mathbf{V}_F,\mathbf{I},q,\mathbf{u}\right)=\max_{t\in[t_k,t_k+T_H]} Q_r \tag{31}$$

is minimized.

At time $t_{k+1} = t_k + T_F$ the procedure is run once again and the storages of the reservoirs $\mathbf{V}_{F\,\mathrm{next}}$ in time $t_{k+1} + T_F$ are determined.

It would be good if the previous results may be used in the next step in order to accelerate the search. At time t_k several controls **u** are selected for several inflows scenarios ($\mathbf{I}$, q) determined in period $[t_k, t_k + T_H]$. On this basis the expected storage $\mathbf{V}_{k+1}$ at time t_{k+1} may be evaluated in time t_k and then used as the first approximation for the search performed in time t_{k+1}. If the difference between sequentially formulated inflow forecasts is not huge the computations might be faster in this way.

5.2 Real-time selection of optimal reservoir outflows

At this level checking times $t_i = t_k + i\,\Delta\tau$ ($i = 1, 2, \ldots, M-1$; $M = T_F / \Delta\tau$) are defined in the forecasting horizon $[t_k, t_k + T_F]$. At any time t_i available information is as follows: the inflows ($\mathbf{I}_{i-1}$, q_{i-1}) and storages $\mathbf{V}_{i-1}$ at time t_{i-1}, past inflows ($\mathbf{I}$, q) which occur in the system until time t_{i-1}, the reservoir storages $\mathbf{V}_i$ at time t_i and the storage $\mathbf{V}_F$ at time $t_k + T_F$.

If $t_i = t_k$ the decision-maker may rely on the inflows forecast specified for the upper long-term algorithm. At any other time t_i the inflows forecast is updated. To update the short-term inflows forecast the number of inverse problems has to be solved.

The periods $\Delta\tau$ is short enough to make an assumption about linear changes of inflows. The reservoirs outflows $\mathbf{u}_{i-1}$ in period $\Delta\tau$ may be constant. Hence, the determination of inflows $\mathbf{I}$ in period $\Delta\tau$ may relay on integration of reservoirs mass balance equations

$$\frac{d\mathbf{V}}{dt} = \mathbf{EI} + \mathbf{Bu} \tag{32}$$

with substitutions

$$\mathbf{V}(t_{i-1}) = \mathbf{V}_{i-1}, \qquad \mathbf{V}(t_i) = \mathbf{V}_i, \qquad \text{and} \qquad \mathbf{I}(t_{i-1}) = \mathbf{I}_{i-1}, \qquad \mathbf{u}_{i-1} = \mathbf{u}_i \tag{33}$$

The results of such a procedure are the real inflows $\mathbf{I}_i$ in time t_i. The formulation of the inverse problem for the determination of inflows q to the uncontrollable part of the system depends on the structure of the model used as the description of this system. However, it may be done explicitly as the procedure for reservoirs inflows described above or implicitly by use of optimization methods for the identification of model boundary conditions. Finally the decision-maker should obtain the inflows to the system in time t_i, that means $(\mathbf{I}_i, q_i)$. Comparing this information with previous assumptions enables him to update the inflows forecast for the next period $[t_i, t_k + T_F]$.

After necessary updates the operational decision problem is as follows: for a given storages $\mathbf{V}_i$ and $\mathbf{V}_F$ and assumed inflow scenario $(\mathbf{I}, q)$ for $[t_i, t_k + T_F]$ find reservoir releases $\mathbf{u}$ in the period $[t_i, t_k + T_F]$ such that state equations with constraints

$$\frac{d\mathbf{V}}{dt} = \mathbf{EI} + \mathbf{Bu}, \tag{34}$$

$$\mathbf{V}(t_i) = \mathbf{V}_i, \qquad \mathbf{V}(t_k + T_F) = \mathbf{V}_F, \tag{35}$$

$$\mathbf{U}_{\min} \le \mathbf{u} \le \mathbf{U}_{\max}, \qquad \mathbf{V}_{\min} \le \mathbf{V} \le \mathbf{V}_{\max}, \tag{36}$$

$$Q_r = \psi(\mathbf{u}, q), \tag{37}$$

are satisfied and the objective function

$$z_2(\mathbf{V}_F, \mathbf{I}, q) = \max_{t \in [t_i, t_k + T_F]} Q_r \tag{38}$$

is minimized.

The assumptions about the inflows $(\mathbf{I}, q)$ in period $[t_i, t_k + T_F]$ may be wrong. The decision-maker is able to correct them after the next period $\Delta\tau$. So, to prevent from dangerous overtopping additional constraint should be added

$$P(\mathbf{V}_{\min} \le \mathbf{V} \le \mathbf{V}_{\max}) = 1 \qquad \text{for } t \in [t_i, t_i + \Delta\tau]. \tag{39}$$

This reliability constraint incorporates global information in the operational control level. $P(A)$ is the probability of the event A determined for all possible inflows scenarios in period $[t_i, t_i + \Delta\tau]$. Formulae (39) means that the decision-maker has to be sure that overtopping will not occur until the next system check.

Due to the inflow uncertainty the global information used to determine storage $\mathbf{V}_F$ at time $t_k + T_F$ may also be wrong. At the operational level the validity of long-term forecasts may be also checked. At time t_{i-1} the controls $\mathbf{u}$ for $t \in [t_{i-1}, t_k + T_F]$ are specified. At the same moment the several inflow scenarios are available from the upper long-term control. The application of controls $\mathbf{u}$ selected in time t_{i-1} may result in different storages $\mathbf{V}_i$ depending on real inflows in period $[t_{i-1}, t_i]$. Hence, a probability distribution describing possible storages of the reservoir $\mathbf{V}_i$ at time t_i may be determined. The acceptable difference between expected and real storages at time t_i related to this distribution may be specified. If the difference between decision-maker expectations and real situation is too large the operation control sequence should be interrupted. Instead of the described above procedure the request for new forecast and storage $\mathbf{V}_F$ should be sent from the lower to upper level control center.

5.3 Real-time information exchange between models

The described algorithm is schematically presented in fig. 5 and 6. The upper part of the algorithm is run in any time t_k. In the fig. 5 the current situation in the catchment is represented by the storages $\mathbf{V}_k$ but it also includes the reservoirs outflows $\mathbf{u}_k$ and water levels observed in the selected points of the system in time t_k. The set of inflows forecasts for the horizon $[t_k, t_k + T_H]$ is provided at time t_k. On this basis the desired storages $\mathbf{V}_F$ for time t_{k+1} are determined. Such information is sent to the lower level algorithm for which the main goal is to determine the reservoir outflows in short horizon $[t_k, t_{k+1}]$.

The lower level algorithm is run several times until next start of upper level procedure. At any time $t_k + i\,\Delta\tau$ for $i = 0, 1, ...$ the situation in the system is checked and the past inflow forecast is verified according to the procedure described in the previous section. After verification the controls for the time horizon $[t_k + i\,\Delta\tau, T_F]$ are updated. On the basis of the inflow forecast provided by the upper level algorithm the acceptable deviation from the assumed system state in time $t_k + (i+1)\,\Delta\tau$ is determined. If the difference between expected storages in time $t_k + (i + 1)\,\Delta\tau$ and real storages is too large, the message is sent to upper part of the algorithm and a new inflow forecast is verified.

The computations are implemented and verified in any time $t_k + i\,\Delta\tau$. The decision-maker has the opportunity to change his/her mind and apply other controls according to the changing situation in the basin. This strategy should guarantee the flexibility which is necessary in uncertain inflow conditions.

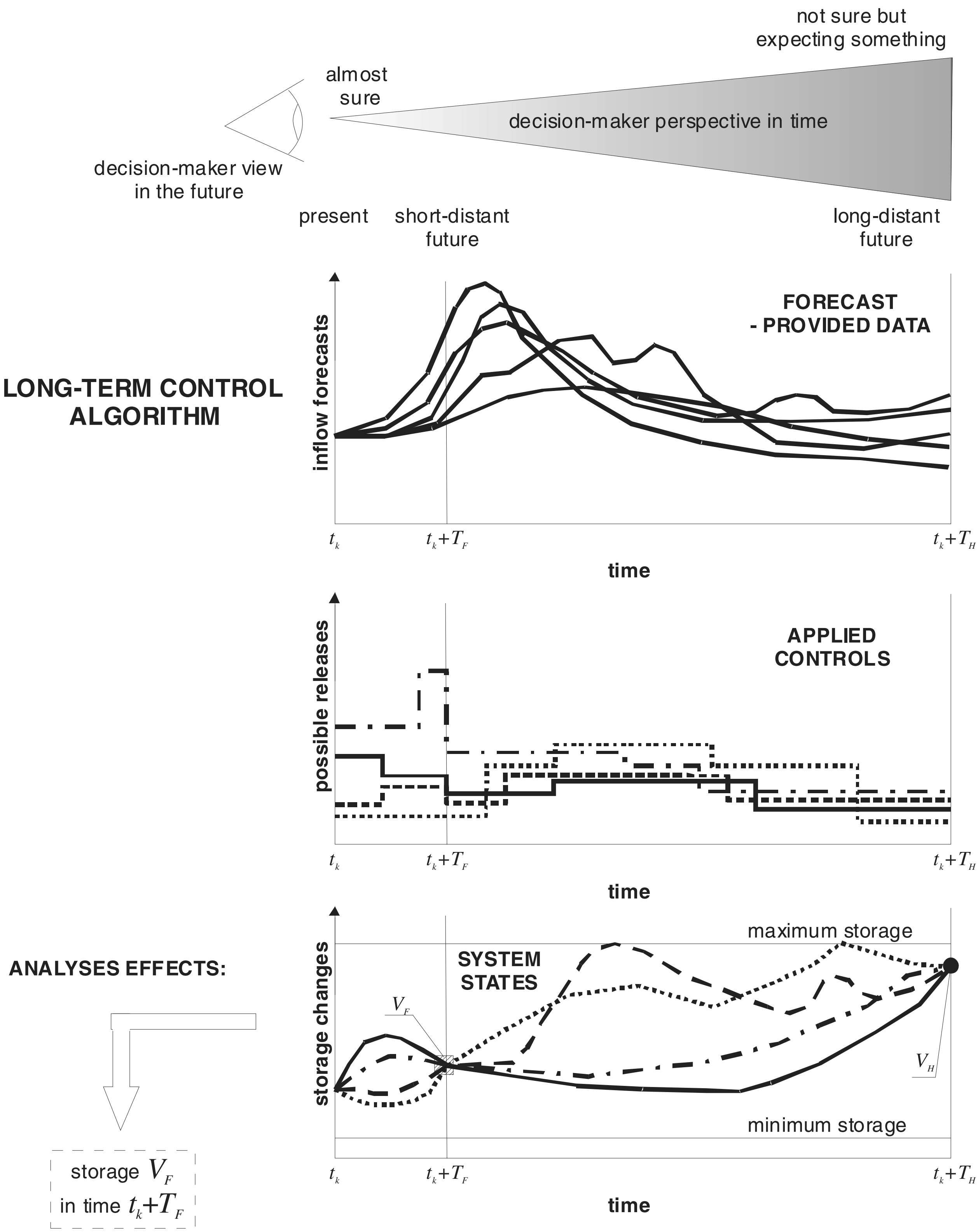

Fig. 5 The idea of long-term control algorithm performance

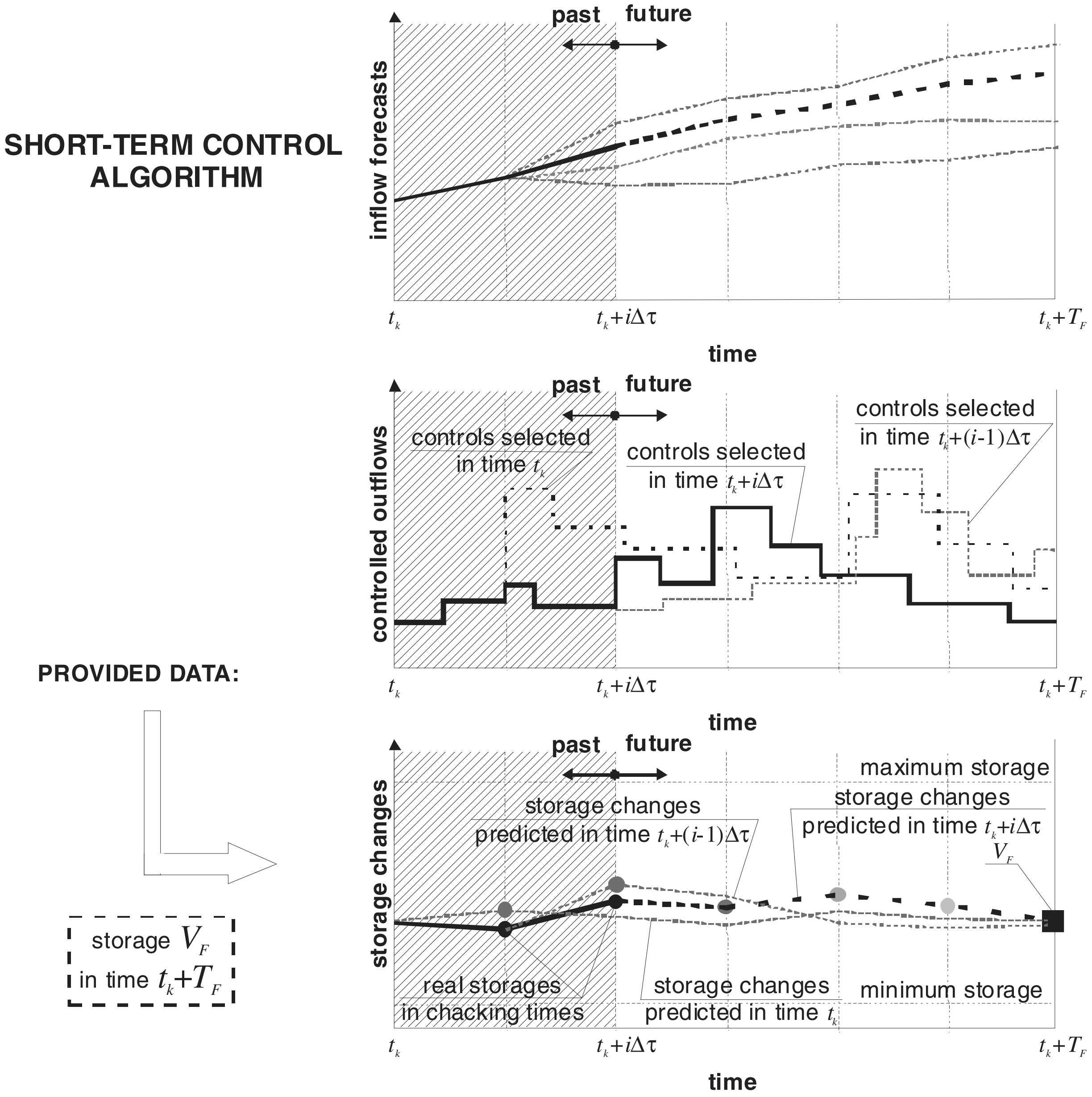

Fig. 6 The idea of short-term control algorithm performance

6. Complexity of the problem and search organization

The issue of high importance in real-time reservoirs management is the time of computations. The decisions have to be made quickly. Hence, the computations should be fast also. It is useless to solve big equations and construct big and time consuming algorithms. The analyzed problem formulated as stochastic minimax optimization at each level is very serious. The solution of the upper or lower level control problem may require application of non-convex nonlinear optimization methods the main characteristic of which is long computational time. Hence, some further simplifications and/or modifications have to be implemented. Fortunately the analysis of the described problem enables such actions resulting with computational time reduction.

First of all, the selected functions **u**, which are continuous in time, may be replaced by the set of parameters describing their changes in the control horizon. The set of parameters may be easily constructed on the basis of engineering reservoir control rules. This problem is described in the next section.

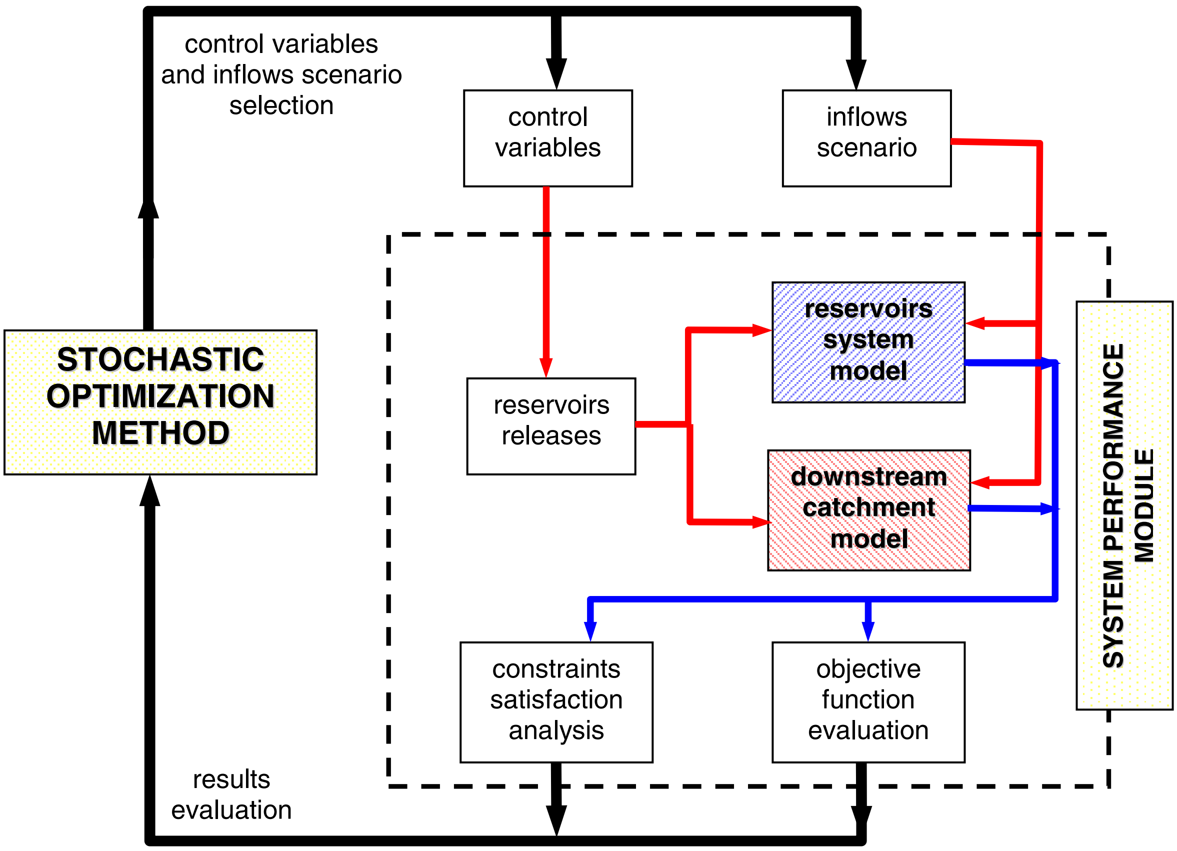

Fig. 7 Basic concept of search procedure organization

Secondly the uniqueness of the equations (3) may be used. For a given controls **u** and specified inflows scenario **I**, the storages **V** at any time t depend only on the initial condition $\mathbf{V}_0$ known in time t_0. The same feature has the nonlinear formulation (9) . If $\mathbf{u}$, $\mathbf{I}$ and $\mathbf{h}_0 = \mathbf{h}(t_0)$ the reservoir water levels $\mathbf{h}$ at time t may be determined uniquely. These features enable the organization of the search as it is shown in fig. 7. The chosen search method has to select a set of parameters describing releases $\mathbf{u}$ and some possible inflow scenario ($\mathbf{I}$, q) in each step of the algorithm. In the next step the reservoir releases $\mathbf{u}$ are computed from the provided parameters. Then the state trajectories are computed using reservoir (3) (or (9)) and catchment models (6) (or (7)). At the last step the objective function value is determined and constraints satisfaction is analyzed. The later information is sent to the optimization method to analyze the fitness of the previously selected parameters.

The next problem are the constraints (5) imposed on the controls $\mathbf{u}$ and state variables $\mathbf{V}$. The proposed ways to deal with constraints are twofold. The set of parameters describing controls $\mathbf{u}$ is constructed in such a way that constraints imposed on $\mathbf{u}$ are satisfied by definition. The constraints imposed on $\mathbf{V}$ are treated in another way. The penalty functions are constructed. The functions are formulated in minimax terms

$$f_{\min j} = \kappa \lambda_V \max_{t \in [t_l, t_l + T]} \max \left\{ 0, V_{\min j} - V_j(t) \right\}, \tag{40}$$

$$f_{\max j} = \kappa \lambda_V \max_{t \in [t_l, t_l + T]} \max \left\{ 0, V_j(t) - V_{\max j} \right\}, \tag{41}$$

where j is the number of reservoir, t_l is the decision-making time, $t_l + T$ is control horizon, κ is the unit penalty and λ_V is the scaling factor. The penalty functions are added to the main objective function.

There are some more opportunities which help in overcoming the complexity of the presented problem. The computations have to be organized in a sequential manner, from step to step. It was mentioned in previous section that the results of the previous step may be incorporated at the upper level control as the initial approximation for the next step. The lower operational part of the algorithm should use the previous step results, too. The special structure of the reservoirs system model enables effective decomposition of the problem. This issue is described in one of the next sections.

7. Design of proper control rules

The key issues in the computational effectiveness considerations is proper description of decisions by a relatively small number of parameters. Hence, the choice of reservoir outflow representation may be crucial. The selected structure of function describing the reservoir releases

$$u_l(t) = f_l(t, \alpha_1, \alpha_2, \ldots) \qquad \text{for } l = 1, 2, \ldots, N \tag{42}$$

should fit the purposes of the system performance. It should also relay on the performance conditions. The most useful observation is that the reservoir operators prefer to work with constant outflows predetermined for some period of time. The simplest way to satisfy this requirement is to divide the control horizon into constant subintervals, then select constant outflow from the reservoir in each support. However, to obtain flexible control rules fitted any probable situation relatively large number of supports is needed. If the supports are of the different lengths selected also during the search, the procedure becomes more complex but the number of necessary parameters decreases significantly. Hence, the number of search method iterations is small, too.

Below two flexible and effective reservoir outflows representations are presented. For the sake of the simplicity it is assumed that control rules are determined on the interval $[0, T_H]$.

7.1 Time Dependent Rectangular Pulses

This technique was tested on the deterministic examples by Dysarz and Napiórkowski (2002a). The release function (42) is described by the set of $2\,NRP - 1$ parameters, where NRP is a number of supports with constant outflow discharge. The function argument is also time t. The function values are evaluated according to following algorithm

$$T_1 = \alpha_1 T_H, \tag{43}$$

$$T_i = (1 - \alpha_i)\, T_{i-1} + \alpha_i T_H \qquad \text{for } i = 2, 3, \ldots, NRP - 1, \tag{44}$$

$$u_i = U_{\min} + \alpha_{NRP+i-1}(U_{\max} - U_{\min}) \quad \text{for } i = 1, 2, \ldots, NRP, \tag{45}$$

and finally the function value is

$$u(t) = u_i \qquad \text{if and only if } t \in [T_{i-1}, T_i] \tag{46}$$

T_i (for $i = 1, 2, \ldots NRP - 1$) are the ends of time subintervals. It is assumed $T_{NRP} = T_H$ and $T_0 = 0$. The discharge u_i (for $i = 1, 2, \ldots NRP$) is constant in each $[T_{i-1}, T_i]$. The formula (45) describes simple selection of value which meets parameter $\alpha_{NRP+i-1}$ in the interval $[U_{min}, U_{max}]$. In formulae (43) and (44) the interval from which value is taken varies with i. For the first interval the time moment T_1 may be selected from the whole control horizon T_H. Next point T_i may be located only in the interval $[T_{i-1}, T_H]$. Such structure is used to prevent from exceeding the constraints

$$T_{i-1} \leq T_i \qquad \text{for } i = 2, 3, \ldots, NRP - 1 \tag{47}$$

The parameters $\alpha_1, \alpha_2, \ldots, \alpha_{2\,NRP-1}$ may have real values from 0 to 1. In the presented illustration (fig. 8) the vector of parameters is organized as follows: the first $NRP - 1$ parameters describes the time moments T_i, the parameters with indexes from NRP to $2\,NRP - 1$ are used to determine the outflow values. The vector of parameters may also be organized in different manner. It should not affect the optimization search.

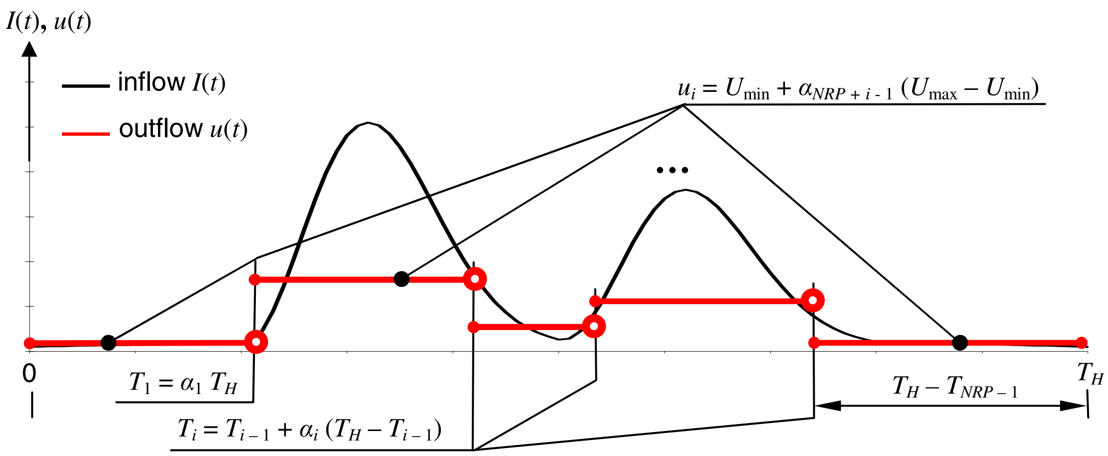

Fig. 8. Simplest control rules illustration – time dependent rectangular pulses

The described procedure is flexible and simple. It enables significant decreasing of the optimization problem dimensionality. Due to the flexibility of the time subintervals the convergence and high accuracy are achieved even for small NRP. However, the selection of NRP may be crucial for some cases because of another problem. If the NRP is too large, chosen optimization method may tends to shorten some of the intervals to the length smaller then time step in simulation part of the algorithm. In such case the searched space has too large dimensionality, inadequate for the solved problem. Additional elements preventing from such processes during search should be incorporated into optimization method.

7.2 Semi-Fixed Rectangular Pulses

The shrinking process may be prevented by one mechanism incorporated directly in the description of the control rules. In this approach the function (42) consists of two sets of parameters describing time moments T_i: fixed and selected during the optimization. In the preliminary computation, before optimization search the fixed time moments are calculated as follows

$$TF_i = i\,\Delta T \qquad \text{for } i = 1, 2, \ldots, NRP - 1, \tag{48}$$

where $\Delta T = T_H / NRP$. Then, during the optimization time moments are determined as follows

$$T_i = TF_i + \alpha_i\,\beta\,\Delta T \qquad \text{for } i = 1, 2, \ldots, NRP - 1, \tag{49}$$

where $\beta \in [0, ½]$ is shrinking coefficient describing the allowed deviation of T_i from TF_i. In this case parameters α_i are the real values varying between -1 and 1.The values of discharges u_i in any time subinterval $[T_{i-1}, T_i]$ and values of discharges at any time t are computed according to the previous formulae (45) and (46), respectively. The rule is illustrated in fig. 9. If $\beta \leq 0.5$ then the constraint (47) is satisfied.

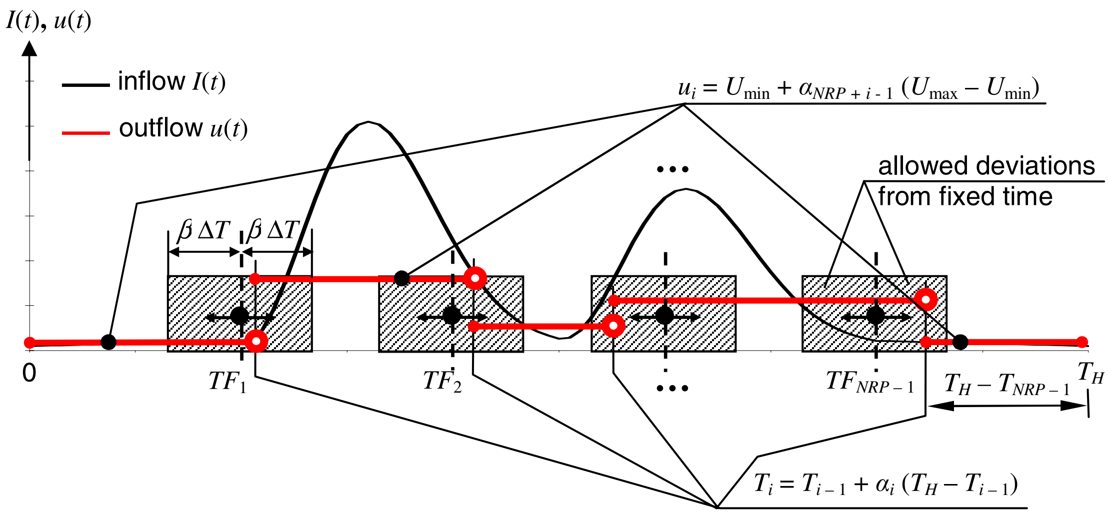

Fig. 9. Control rule of type semi-fixed rectangular pulses – main idea

8. *Sequential storage balance technique*

The presented control problem is quite complex. In almost each level of the presented procedure optimal search is needed. Even if effective control rules described in above chapter are implemented the dimensionality of the task is still large. The sufficient decomposition technique based on the specific features of the system can decrease the number of necessary computation. The main idea of the technique presented here is based on the sequential changes of only one reservoir storage in the system. The rest of system parameters may be evaluated from linear state equations (3).

There are two preliminary assumptions posed in the beginning of the single search with index p. The first states that the admissible control rules defined in certain period of time $[0, T_H]$ are known. The second is related to the inflow scenarios. The single search is preformed for the one selected inflow scenario. In next algorithm step $p + 1$ should improve the performance of the system by changing only one reservoir storage. Lets denote this reservoir index by j. Hence, it may be written

$$V_l^{(p)} = V_l^{(p+1)} \qquad \text{for all } l \neq j \tag{50}$$

and

$$V_j^{(p)} \neq V_j^{(p+1)}. \tag{51}$$

If the initial state of the system $\mathbf{V}(t = 0) = \mathbf{V}_0$ is known, the above formulas may be replaced by formulae relaying on derivatives

$$\frac{dV_l^{(p)}}{dt} = \frac{dV_l^{(p+1)}}{dt} \qquad \text{for all } l \neq j \tag{52}$$

and

$$\frac{dV_j^{(p)}}{dt} \neq \frac{dV_j^{(p+1)}}{dt}. \tag{53}$$

For further considerations the difference between reservoirs in parallel an reservoirs in series is important. The description of the one reservoir in parallel system has following form

$$\frac{dV_j}{dt} = I_j - u_j \qquad \text{for any } j = 1, 2, \ldots, N. \tag{54}$$

For the known deterministic inflow I_j the storage V_j is modified only by changing the reservoir outflow u_j. Hence, if the V_j is changed, it cannot affect any other reservoir in the system. The described observation is graphically presented in fig. 10.

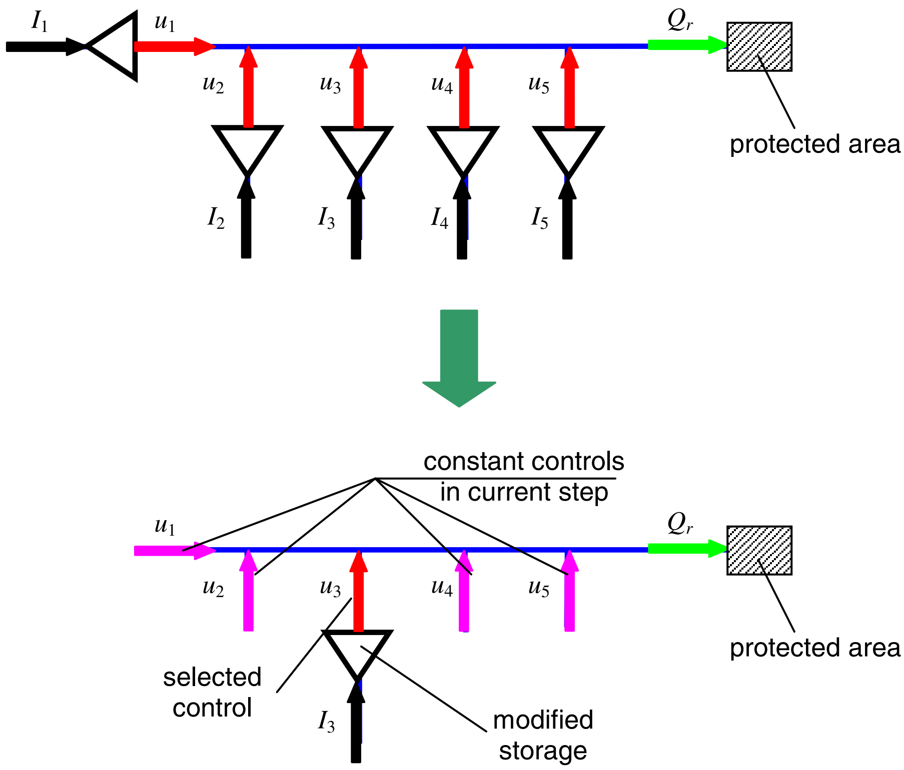

Fig. 10 Reduction of the problem during single algorithm step
for the system of reservoirs in parallel

The equations for the reservoirs in series may be written as

$$\frac{dV_1}{dt} = I_1 - u_1, \tag{55}$$

$$\frac{dV_j}{dt} = u_{j-1} + I_j - u_j \qquad \text{for } j = 2, 3, \ldots, N. \tag{56}$$

So, in deterministic case with fixed inflow I_j the change of j-th reservoir storage imposes the change of control either u_{j-1} or u_j. To satisfy the constraint (50) or (52) only u_j may be changed. Such modification does not affect the reservoirs located in the system above j-th. It means reservoirs with numbers $l = 1, 2, \ldots, j-1$. However, the summarized inflows to reservoirs located below $u_{l-1} + I_l$ (for $l = j+1, j+2, \ldots, N$) are influenced by any change in u_j. If the constraint (50) (and (52)) is satisfied outflow u_l ($l = j+1, j+2, \ldots, N$) from each reservoir located below has to be modified, too.

The necessary modification of outflows from the downstream reservoirs u_l may be derived from the mass balance equations of reservoirs with numbers

$l = j + 1, j + 2, \ldots, N$. Lets denote the new outflow from reservoirs j-th in iteration $p + 1$ as follows

$$u_j^{(p+1)} = u_j^{(p)} + \Delta u_j^{(p+1)}, \tag{57}$$

where $\Delta u_j^{(p+1)}$ is the difference between outflows from reservoir j-th in iterations p and $p + 1$. Because the outflows from the upstream reservoirs ($l = 1, 2, \ldots, j - 1$) are not changed, the mass balance equation for the j-th reservoir in iteration $p + 1$ is written as

$$\frac{dV_j^{(p+1)}}{dt} = \frac{dV_j^{(p)}}{dt} - \Delta u_j^{(p+1)}. \tag{58}$$

For the reservoir $j + 1$ one may write similarly

$$\frac{dV_{j+1}^{(p+1)}}{dt} = \frac{dV_{j+1}^{(p+1)}}{dt} + \Delta u_j^{(p+1)} - \Delta u_{j+1}^{(p+1)} \tag{59}$$

Taking into account (52) leads to

$$\Delta u_j^{(p+1)} = \Delta u_{j+1}^{(p+1)} \tag{60}$$

Repeating these derivations for all downstream reservoirs $l = j + 1, j + 2, \ldots, N$ gives

$$\Delta u_l^{(p+1)} = \Delta u_j^{(p+1)} \tag{61}$$

As it is well visible the problem defined for the system of reservoirs reduces to the control of single reservoir in subsequent iterations. The formulation of the problem is considered for one inflow scenario ($\mathbf{I}$, q). Assuming that the outflows $\mathbf{u}^{(p)} = \left[u_1^{(p)}, u_2^{(p)}, \ldots, u_N^{(p)}\right]^{\mathrm{T}}$ in iteration p are known, the first step is to select the reservoirs j-th. Then in iteration ($p + 1$) state equations and the constraints written for the system of reservoirs in parallel are reduced to the following

$$\frac{dV_j^{(p+1)}}{dt} = \frac{dV_j^{(p)}}{dt} - \Delta u_j^{(p+1)} \tag{62}$$

$$Q_r^{(p+1)} = \psi\left(\mathbf{u}^{(p+1)}, q\right), \tag{63}$$

$$U_{\min j} - u_j^{(p)} \le \Delta u_j^{(p+1)} \le U_{\max j} - u_j^{(p)}, \tag{64}$$

$$V_{\min j} \le V_j^{(p+1)} \le V_{\max j}, \tag{65}$$

where $\mathbf{u}^{(p+1)} = \left[u_1^{(p)}, u_2^{(p)}, \ldots, u_{j-1}^{(p)}, u_j^{(p)} + \Delta u_j^{(p+1)}, u_{j+1}^{(p)} \ldots, u_N^{(p)}\right]^{\mathrm{T}}$. In the case of reservoirs in series it looks similarly

$$\frac{dV_j^{(p+1)}}{dt} = \frac{dV_j^{(p)}}{dt} - \Delta u_j^{(p+1)} \tag{66}$$

$$Q_r^{(p+1)} = \psi\left(\mathbf{u}^{(p+1)}, q\right), \tag{67}$$

$$U_{\min j} - u_j^{(p)} \leq \Delta u_j^{(p+1)} \leq U_{\max j} - u_j^{(p)}, \tag{68}$$

$$U_{\min l} - u_l^{(p)} \leq \Delta u_j^{(p+1)} \leq U_{\max l} - u_l^{(p)} \qquad \text{for } l = j + 1, j + 2, ..., N, \tag{69}$$

$$V_{\min j} \leq V_j^{(p+1)} \leq V_{\max j}, \tag{70}$$

The situation in the single step $(p + 1)$ is presented schematically in fig. 11.

In both cases the forms of objective function and additional constraints depend on the algorithm level as it was described in previous section. In iteration $(p + 1)$ the differences $\Delta u_j^{(p+1)}$ between outflow from reservoir j-th in iteration p and $(p + 1)$ have to be determined. After this step the outflows from the system of reservoirs are recalculated according to following rules

- in the system of reservoirs in parallel

$$u_l^{(p+1)} = \begin{cases} u_l^{(p)} & l \neq j \\ u_l^{(p)} + \Delta u_j^{(p+1)} & l = j \end{cases} \tag{71}$$

- in the system of reservoirs in series

$$u_l^{(p+1)} = \begin{cases} u_l^{(p)} & l \leq j - 1 \\ u_l^{(p)} + \Delta u_j^{(p+1)} & l \geq j \end{cases} \tag{72}$$

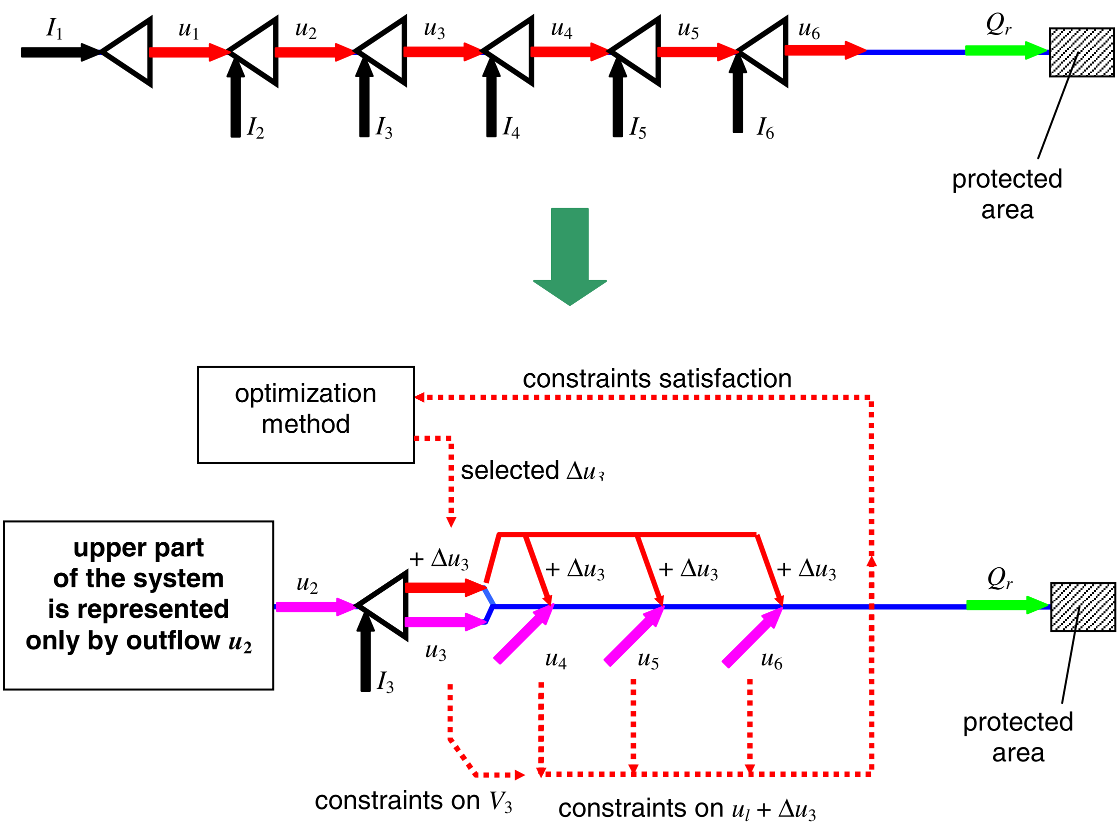

Fig. 11 Reduction of the problem during single algorithm step for the system of reservoirs in series

It was mentioned that the outflows variability in time has special form. The functions representing releases are constant in specified time periods. Due to that fact the differences $\Delta u_j^{(p+1)}$ are constant in some time periods. They are selected according to the rules described in previous subsection. However, there might be two differences. The time intervals selected as a period of constant values of $u_j^{(p)}$ or $\Delta u_j^{(p+1)}$ may not be the same. The coefficients describing the values of $\Delta u_j^{(p+1)}$ magnitudes may be also negative.

In described above way the water storage of reservoirs is balanced sequentially from iteration to iteration. The outflows from reservoirs are improved according to the specified objective function in certain control horizon. The main idea of the procedure is presented in fig. 12. The data provided to the algorithm at the beginning are initial controls. Then the first reservoir is selected and the optimization search is started. After search the controls are updated and next reservoir may be selected. The procedure is repeated until the performance of the whole system is accepted.

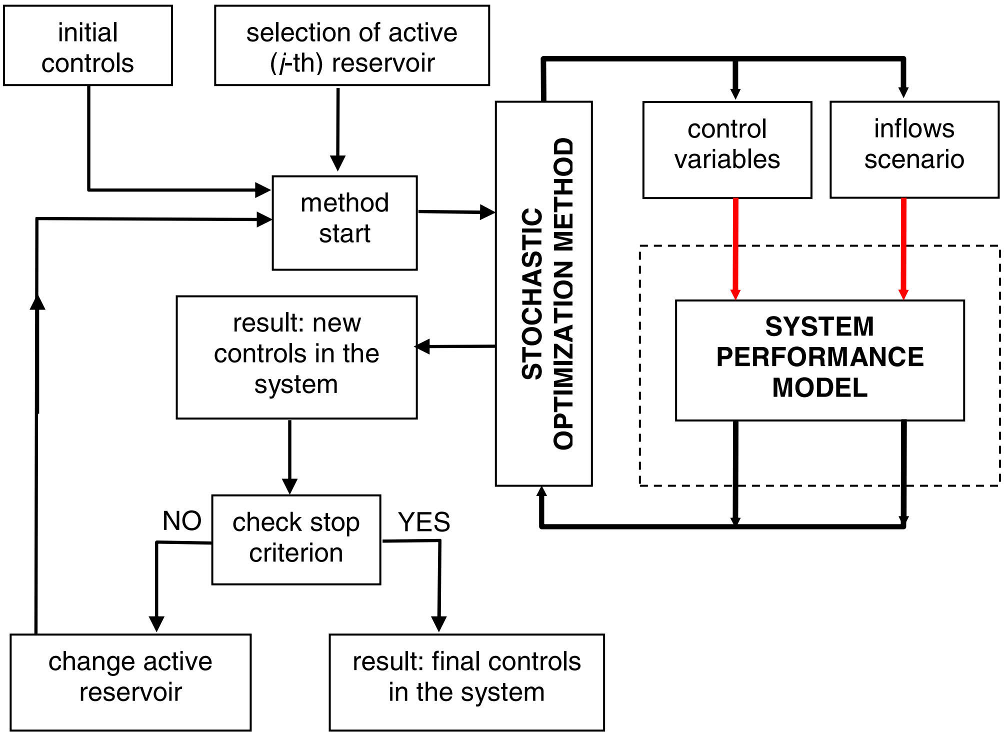

Fig. 12 The concept of sequential storage balance technique

9. *Basic tests*

The sequential water balance technique described above was tested on the artificial deterministic case. The considered system consists of four reservoirs in series according to fig. 1. It was assumed that the protected area is located just below the last fourth reservoir. Hence, the description of the problem consists of state equations (3) and constraints (5). The objective function is formulated as (2).

Each reservoir storage may vary between 20 and 120 million m^3. The initial state is $V_j(t_0) = 20$ million m^3 for each j. At the end of control horizon all reservoir should be full of water $V_j(t_0 + T_H) = 120$ million m^3. Assumed control horizon is rather long, $T_H = 600$ h. The inflow to each reservoir is single flood wave.

TD-RP technique was applied as reservoir control rules. Controlled random search method (Price, 1987; Dysarz i Napiórkowski, 2002b) was used as optimization solver. The active reservoirs were chosen in order from lower to upper. The penalty functions of type (40) and (41) were used to deal with constraints.

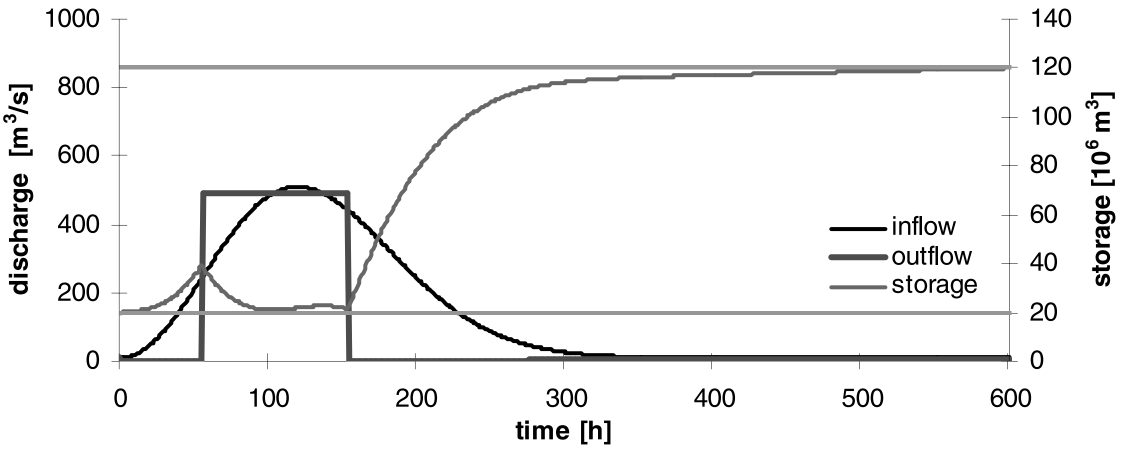

Fig. 13 Performance of the reservoir no. 1

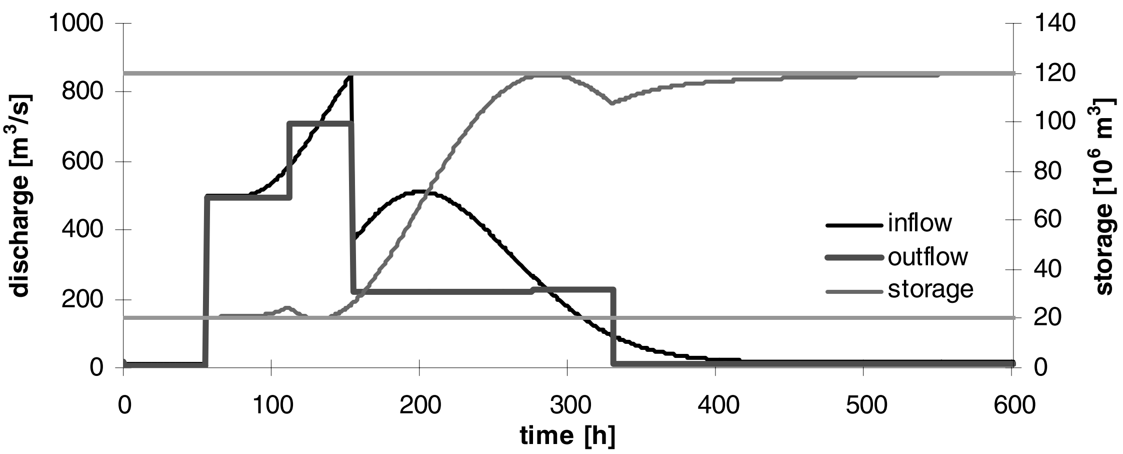

Fig. 14 Performance of the reservoir no. 2

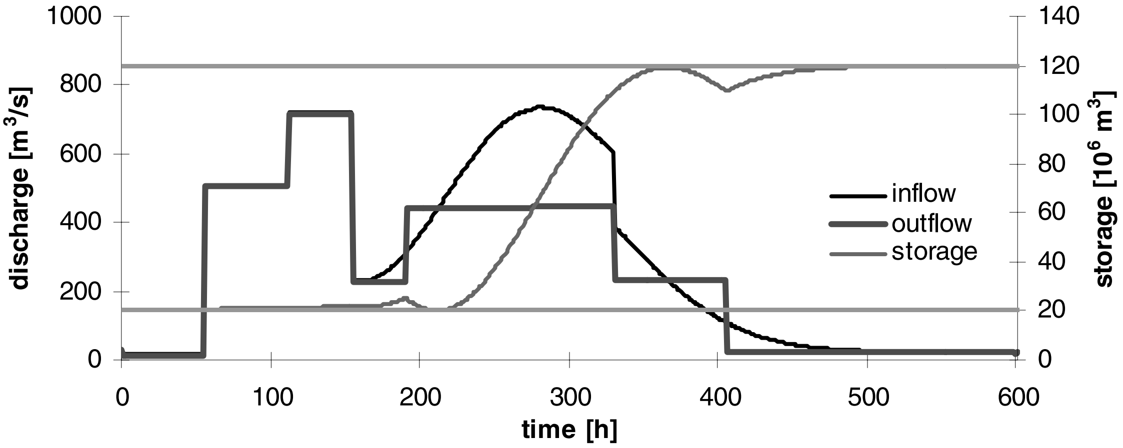

Fig. 15 Performance of the reservoir no. 3

The obtained results were presented in fig. 13 – 17. The first four figures illustrates the performance of each reservoir. The black line is total reservoir inflow equal to inflow I_j and the outflow from upper reservoir u_{j-1}. The red line represents applied control rules u_j. Blue line is the reservoir storage V_j. The gray lines represents the storage constraints, $V_{\min j}$ and $V_{\max j}$. The last figure shows the flows in the protected area. Brown line is the fourth lowest reservoir outflow u_4. This outflow was compared with the flow below the system if no control is applied (black line). Red and dark blue lines represents flow peaks of controlled and uncontrolled flows, respectively.

The figures show that the method performs quite well. The constraints are satisfied and the desirable storage at the end of control horizon is reached. The reduction of flow peak is significant as it was marked in fig. 17.

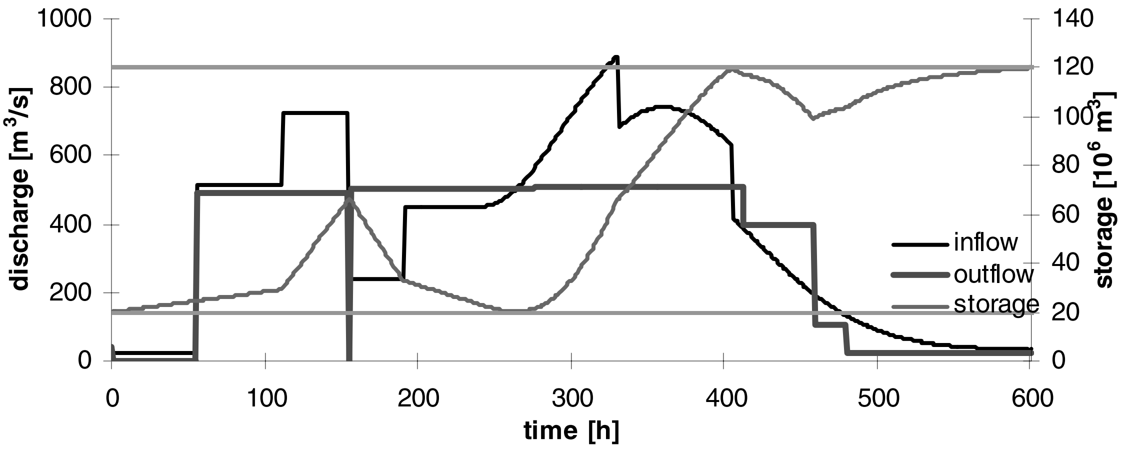

Fig. 16 Performance of the reservoir no. 4

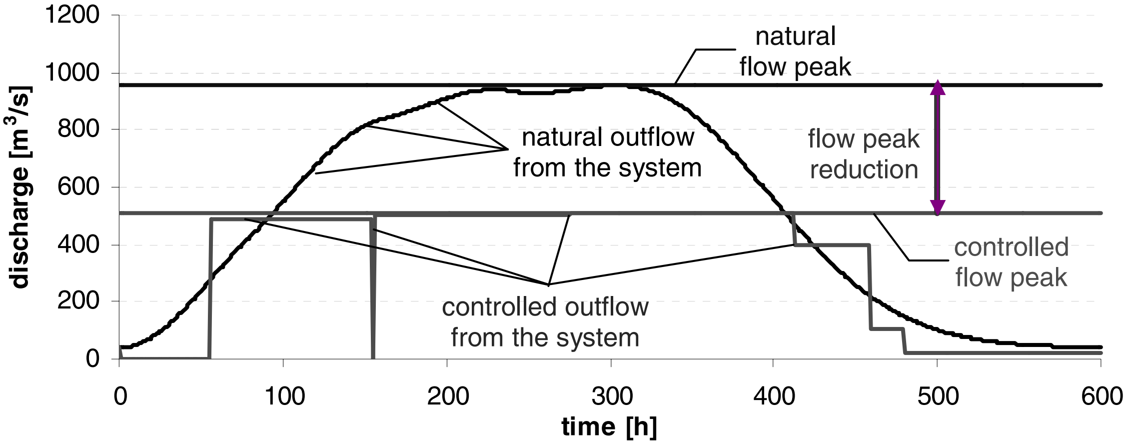

Fig. 17 Natural and controlled outflows from the system - comparison

10. Selected approaches to minimax optimization

Each level of the presented algorithm requires minimax optimization. It is not a standard optimization problem. The objective function is nonlinear and non-convex. The classic optimization methods developed for convex problems may fail in general. A special approach to this task is needed. As it was shown in the one of previous sections the constraints may be easily replaced by the penalty functions of the type (40) – (41). The penalty functions are also formulated in terms of minimax performance index and they may be added to the main objective function. Then one can obtain the problem of the form

$$\min_{\boldsymbol{\alpha}} \max_{t,j} f_j\left(\boldsymbol{\alpha}, t\right), \tag{73}$$

where t represents time in considered control horizon, α is the vector of control parameters.

The basic approach to the described problem is the application of the global optimization method designed to solve deeply nonlinear and non-convex problems. There is many such methods described in the literature. The most simple is to search in the regular grid and sequential decreasing of the domain. This method is very slow and it should not be recommended as a solver for a real-time operational decision support system. In the other methods some random mechanisms are incorporated to accelerate the search process. Some of the most interesting examples are the Monte Carlo methods, simulated annealing, Griewank method, controlled random search or genetic algorithms. One of these methods namely controlled random search developed by Price (1987) was shortly described in the previous report (Dysarz, 2003). This method was implemented as an element of the basic algorithm for the direct solution of (73) in deterministic case. The results were presented in Dysarz and Napiórkowski (2002b). Controlled random search applied directly to the problem (73) is able to provide good results in reasonable time.

The disadvantage of the direct approach to minimax problems by application of the random global optimization method is long computational time. In the mentioned example the controlled random search method performed quite well with exceptions of some runs where the methods jumped into deep local minimum. Global methods are able to overcome this problem, but there is no guarantee that the local minimum is left in any case. However, in general the very fast speed of the calculations should be guaranteed for the purpose of real-time operational management.

The described above method is not only an approach which helps us overcome the complexity of the presented optimization problem, there are also different methods based on the problem transformation. Their advantage is that they modify the problem in such a way that the considered optimization task is smooth and convex. Hence, the classic methods may be implemented. This means shorter computational time without loss of accuracy. Here some of them will be shortly presented.

The equivalent formulation of the problem (73) is as follows: find minimum $p \in R$ and proper vector α such that the constraints

$$f_j(\boldsymbol{\alpha},t) - p \leq 0 \tag{74}$$

are satisfied for each j at any moment t. The problem may be also written as single performance index (Polak et. al., 2003)

$$\min_{\boldsymbol{\alpha},p} \left\{ p \middle| f_j(\boldsymbol{\alpha},t) - p \leq 0 \right\}. \tag{75}$$

The above formulation results in standard nonlinear programming problem. The task (75) was investigated by several authors, for example Charalambous and Conn (1978), Han (1981), Vardi (1992), Di Pillo et. al. (1993).

There are also regularization approaches led to smooth approximations of (73). Some examples are presented by Zang (1980), Bertsekas (1982) or Mayne and Polak (1984). The main advantage of smoothing techniques is the transformation of minimax problem of type (73) into a smooth problem that can be solved by a classic optimization method. The disadvantage of such an approach may be possible ill-conditioning of the resulting smooth task (Polak et. al., 2003). The solver used in such a case should be specifically selected to overcome these difficulties. An interesting approach was described by Polak et al. (2003). Following the derivations described there the problem (73) should be replaced by

$$\min_{\boldsymbol{\alpha}} \log \left\{ \frac{1}{p} \sum_{j} \int_{t} \exp\left[p f_j \left(\boldsymbol{\alpha}, t \right) \right] dt \right\} \tag{76}$$

where p is smoothing parameter. When $p \to \infty$ then problem (76) approximates (73). The algorithm prepared to solve (76) and several examples are given by Polak et. al. (2003). Implementation of this technique in the considered reservoir control problem seems to be possible.

11. Concluding remarks

The main goal of this report is to present the concept of uncertainty reduction in operational reservoirs management in flood endangered conditions. The area of this research is very important for the national economy in many countries. Floods cause huge damages to the people and industry all around the world. Many researchers try to deal with different aspects of reservoir management. However, there is still a lack of coherent ideas enabling operational flood management and loses reduction. The main reason for this is the computational complexity of the problem. The control criterion is of the minimax form. The optimization methods used to solve the problem have to be designed in such a way that specific features of the task are taken into account. The most important are non-linearity and non-convexity of the objective function.

The useful description of large and spatially distributed reservoirs systems consists of differential equations and algebraic constraints in the form of inequalities. The reservoirs systems are divided into two basic tapes. These are reservoirs in parallels and in series. The slight difference in the mathematical description between these two groups causes some differences in proper treatment during operational management. An example of different approaches for both systems is visible when the system is decomposed. The uncertainty of inflows to the system is the reason for stochastic treatment of reservoir performance.

Te problem of inflow uncertainty and reliable inflow forecasts is the key factor in the presented approach. The disastrous floods that occurred in the last years aroused interest in rainfall forecasting and rainfall-runoff modeling. Especially some results obtained in the EFFS projects sponsored by European Commission are promising and may be used in the future as the basis for control of reservoirs in uncertain inflow conditions. It is assumed such results are available for the presented procedure of the system control during floods.

The main idea of the algorithm enabling control of the reservoir system is based on the observations about present reservoir management and development of highly sophisticated optimization methods. This approach is extended and formulated in mathematical terms. It consists of two computational levels: upper and lower. In the upper part of the procedure the long-term flow conditions are analyzed. The necessary data includes 10-11 days inflows forecasts. The results of the analysis are desired storages which should be reached in the system in time for the next forecast update. These are the main constraints for the lower part of the procedure where only short-term strategies are selected. The complexity of the posed stochastic optimization problems is important.

Some simplifications are proposed. Proper representation of reservoir outflow and decomposition of the problem might be very useful for the purpose of dimensionality and complexity reduction. As it is presented the problem of reservoirs system control is reduced to the problem of single reservoir control in following iterations. The example with four reservoirs in a series is presented. The procedure converges step by step in reasonable time. The minimax criterion may also be simplified. Some concepts of the minimax problem reformulation are presented. Such procedures may reduce the complexity of the problem. The main idea of applied methods is the approximation of the not-convex optimization problem by a convex one. The convergence of such approaches was analyzed and proved by a few researchers.

As it is shown the decision-maker dealing with reservoirs management during a flood has a difficult task. The basis for the decision support system enabling control of the system has been presented and tested on simplified examples. Although, the problem is complex some simplifications might be implemented. Finally the complexity of the problem may be overcome. The time of computations should be reduced and algorithms may be used in real-time operational conditions.

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