Water Asset Management Strategy based on Predictive Rainfall/Runoff Model to Optimize the Evacuation of Water to the Sea

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Abstract: Hydrographical networks are large scale systems that are used to answer to the Human uses. They are impacted by extreme events that should be bigger due to climate change. By focusing on extreme rainy events, the amount of water in excess has to be dispatched on all the network to avoid flood, and then rejected to the sea heeding the tides. Pumps can also be used to reject the water to the sea but they lead to big operating cost. To deal with this challenging issue, the modelling tools and the water asset management strategies that have been recently proposed are adapted and improved in this paper. They consist in an integrated model, a flow-based network and a quadratic optimization based on constrains. The efficiency of this water management strategy requires an accurate predictive rainfall/runoff model. It is highlighted by considering a realistic case study that is also used to describe all the methodology step.

1 INTRODUCTION

Transport via inland waterways benefits of economic and environmental advantages (Kara et al., 2015; Mihic et al., 1993; Mallidis et al., 2012; Brand et al., 2012). However, the inland waterways will be strongly impacted by climate hazards (Koetse and Rietveld, 2009; EnviCom, 2008; IWAC, 2009). It is confirmed by the studies in (Arkell and Darch, 2006), (Wang et al., 2007) and (Jonkeren et al., 2007) that focus on inland waterways in UK, in China and on the Rhine respectively. The frequency and intensity of future flood events are expected higher (Bates et al., 2008; Boé et al., 2009; Ducharne et al., 2010). To deal with the management of inland waterways in a climate change context, a multi-scale management architecture has been proposed in (Duviella et al., 2013) and developed in (Nouasse et al., 2016b), allowing the use of modelling approaches and management strategies for water level control (Segovia et al., 2017; Horvàth et al., 2014b; Horvàth et al., 2015a; Horvàth et al., 2015b; Rajaoarisoa et al., 2014), and water volume allocation (Nouasse et al., 2015; Nouasse et al., 2016a). However, it has been shown that even if it is possible to control the hydraulic structures with efficiency by considering a deterministic problem, uncontrolled intakes and withdrawals have a strong influence on this optimization. It is particularly the case for rainy events that have big influence on inland waterways. Moreover, inland waterways with outlet to the sea have not been considered. This implies a new challenging issue that requires to take into account the effect of the tide and the electrical cost of the pumps during the design of the water management strategies.

The management strategy that consists in an optimal adaptive allocation planning of water resource is adapted and improved in this paper by dealing with inland waterways with outlet to the sea. The influence of the tide has taken into account. A criterion to minimize is defined based on the configuration of the inland waterways, the priorities on water intakes and withdrawals, the management objectives, the tide and the predicted volumes that come from rainy events. The requirement of an accurate prediction of the amount of water volumes that comes from rain is highlighted by considering a realistic case study.

The modelling tools and the optimal allocation planning approach are described in the first section. In the second section, a state of the art of existing predictive rainfall/runoff models is presented. Then, a case study allows illustrating all the step to implement the designed tools and strategy is proposed in the third section. This case study is used to highlight the importance of the rainfall/runoff models during the optimization of the water resource planning.

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2 WATER ASSET MANAGEMENT STRATEGY

2.1 Integrated Model

An integrated model that is linked with a flow-based network has been proposed in (Nouasse et al., 2016b) to deal with inland navigation networks. It aims at modelling the dynamics of each Navigation Reach (*NR*), *i.e.* a part of the canal located between two locks, as a tank with a sample time of several hours. It allows taking into account all the inputs and outputs, controlled or not, of each *NR*. For inland waterways with links to the sea, it is necessary to define a new element representing the output of the integrated model. The model consists in considering a finite number η of interconnected *NR* that are linked following the configuration of the network (*see* Figure 1.a). Each *NR* is numbered and denoted NR_i, with $i \in 1$ to η.

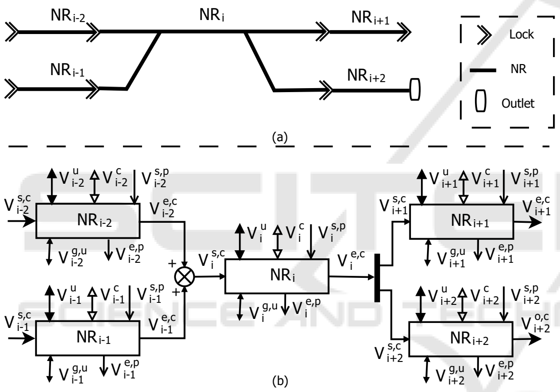

Figure 1: (a) Inland navigation network, (b) corresponding model.

Each NR_i is supplied and emptied by controlled water volumes from locks, controlled gates and pumps when they are available, and by uncontrolled water volumes from water intakes, rain, or exchanges with groundwater. Moreover, the network can be emptied thanks to the outlets to the sea. The set of controlled water volumes is:

1. controlled volumes from one or several upstream *NR* that supply NR_i, denoted $V_i^{s,c}$ (s: supply, c: controlled),
2. controlled volumes from NR_i that empty it, denoted $V_i^{e,c}$ (e: empty),
3. controlled volumes from water intakes that supply or empty NR_i, denoted V_i^c. These volumes are signed; positive if NR_i is supplied, negative otherwise,
4. controlled volumes from pump that supply NR_i, denoted $V_i^{s,p}$ (s: supply, p: pumped),
5. controlled volumes from pump that empty NR_i, denoted $V_i^{e,p}$.
6. controlled volumes that empty NR_i to the sea, denoted $V_i^{o,c}$ (o: outlet).

The set of uncontrolled water volumes is:

1. uncontrolled volumes from natural rivers, rainfall-runoff, Human uses, denoted V_i^u (u: uncontrolled). These volumes are signed depending on their contribution to the volume $V_i(k)$ in NR_i.
2. uncontrolled volumes from exchanges with groundwater, denoted $V_i^{g,u}$ (g: groundwater). These volumes are also signed.

The dynamic volume of NR_i is computed according to the set of controlled and uncontrolled water volumes:

$$V_i(k) = V_i(k-1) + V_i^{s,c}(k) - V_i^{e,c}(k) + V_i^c(k) + V_i^{s,p}(k) \\ - V_i^{e,p}(k) + V_i^u(k) + V_i^{g,u}(k) - \delta_i V_i^{o,p}(k), \tag{1}$$

where k corresponds to the current period of time and $k-1$ the last one with T_M the sample time that corresponds to several hours and δ_i a variable equal to one when outlet is available, equal to zero otherwise.

2.2 Flow-based Network

A flow-based network is designed according to the integrated model as $\mathcal{G} = (\mathcal{N}, \mathcal{A})$, where $\mathcal{N}$ is the set of ordered nodes (vertices) and $\mathcal{A}$ the set of arcs (directed edges). The set of nodes is composed of a common source vertex O without incoming edges, a common sink node without outgoing edges, denoted S (*see* Figure 2), and a node for each NR_i. The total number of nodes is $\eta = card(\mathcal{N}) + 2$.

An arc links two nodes and is defined as a couple $a = (i, j)$, $a \in \mathbb{R}^\alpha$ with $\alpha = card(\mathcal{A})$, where i and j are the origin and destination node of the edge respectively. For networks with outlet to the sea, it is necessary to consider several arcs between the corresponding *NR* and the sink node S. Indeed, the water volumes can be rejected by gravity or thanks to the pumps with not the same cost. Therefore, these arcs are defined as couple $a^\nu = (i, S)$, $a^\nu \in \mathbb{R}^\alpha$ with $\alpha = card(\mathcal{A})$, where i is the origin node and $\nu \in \{1 : m\}$ with m the number of arcs between these two nodes.

The water volume that is transferred between two nodes is represented by a flow associated to each arc a, such as $\phi_a(k) = \phi_{ij}(k)$ with i and j the indexes of the nodes. Here again, it is necessary to consider several flows $\phi_{iS}^\nu(k)$ between the NR_i and the sink node S. The exchanged water volumes are limited by physical characteristics of the hydraulic devices. Hence,

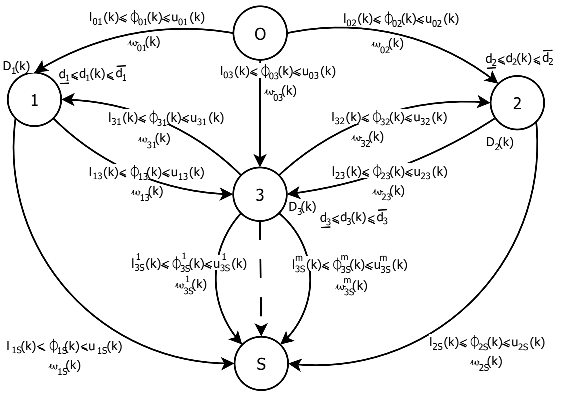

Figure 2: Flow graph composed of three *NR* with one outlet.

dynamical boundary constraints are considered such as $l_{ij}(k) \leq \phi_{ij}(k) \leq u_{ij}(k)$, where $l_{ij}(k)$ and $u_{ij}(k)$ are the lower and upper bound constraints respectively; with $l^{\nu}_{iS}(k) \leq \phi^{\nu}_{iS}(k) \leq u^{\nu}_{iS}(k)$ for the arcs between NR_i and S.

The dynamical cost $\omega_{ij}(k) \in \mathbb{R}^{\alpha}$ that is associated to each arc a is denoted $\omega^{\nu}_{iS}(k)$ for arcs between NR_i and the outlet to the sea. These costs constant on the period k, can be different between k and $k+1$. They allow taking into account a smaller cost for an arc that corresponds to a water transfer by gravity comparing to an arc that corresponds to a water transfer by pump.

The boundary constraints are computed in volume ($[m^3]$) according to the device characteristics (gate, lock, pump...), the time period T_M following some rules that are well described in (Duviella et al., 2016). They have to reflect real behaviour of the inland navigation networks.

Considering the nodes, with the exception of O and S, a relative objective capacity $D_i(k)$, with $i \in \mathcal{N} - \{O,S\}$ is assigned to each of them. It is equal to 0. The current capacity in the node NR_i, denoted $d_i(k)$, has to be equal to $D_i(k)$. It is computed as:

$$d_i(k) = d_i(k-1) + \phi_{a^+}(k) - \phi_{a^-}(k) \text{ for } i \in \mathcal{N} - \{O,S\}, \tag{2}$$

where a^+ is the set of arcs entering the node i, a^- the set of arcs leaving the node i, and $d_i(k)$ the capacity of the node i for the last period. That means that at each time the amount of water entering in the node NR_i has to be equal to the amount of water leaving the node. However, an interval around the objective $D_i(k)$ is allowed leading to $\underline{d}_i \leq d_i(k) \leq \bar{d}_i$, with $\underline{d}_i$ and $\bar{d}_i$ the lower and upper bound constraints. Then, the capacity $d_i(k)$ can be negative or positive. When $d_i(k)$ is negative (respectively positive) at time k, NR_i requires more (resp. less) water at time $k+1$. Even if the objective conditions can not be reached at each time, the capacities $d_i(k)$ have to be closest as possible to their objective. Hence, a dynamical cost function $W_i((D_i(k) - d_i(k))^2)$, $i \in \mathcal{N} - \{O,S\}$ is associated to each capacity $d_i(k)$. This function aims at penalizing the gap between the current capacity $d_i(k)$ and the objective $D_i(k)$. Thus, the optimal water management consists in satisfying the objectives of each node, *i.e.* $D_i(k)$, by optimizing the flows $\Phi(k)$ in terms of minimal cost; the vector $\Phi(k)$ contains the set of flows $\phi_{ij}(k)$, $\Delta(k)$ the set of capacities $d_i(k)$ at time k.

2.3 Optimal Allocation Planning

The objective of the optimal allocation planning consists in determining the optimal sequence of flows Φ to guaranty the objectives $D_i(k)$ (Duviella et al., 2016). It is based on the minimization of an objective criterion for each management step:

$$J_V(k) = \sum_{i}^{\eta} W_i((D_i(k) - d_i(k))^2) + \sum_{a}^{\alpha} \omega_a(k) \cdot \phi_a(k), \tag{3}$$

with k the current step time, η the number of nodes without nodes O and S, and α the number of arcs. That includes arcs between NR_i and S, where the cost is computed as $\sum_{\nu=1}^{m} \omega^{\nu}_{i,S}(k) \cdot \phi^{\nu}_{i,S}(k)$. Note that the value of $d_i(k)$ depends on $d_i(k-1)$ and on the flows $\phi_a(k)$. First terms in equation 3 correspond to the cost due to the gap between the capacity $d_i(k)$ and the objective D_i. This cost can be expressed as a quadratic function. Second terms are the cost of each flow.

The quadratic programming method *quadprog* in Matlab is used to minimize $J_V(k)$ under the equality constraints defined for each flow and each capacity:

$$\min J_V(k) \text{ such that } \begin{cases} L_b(k) & \leq x(k) \leq U_b(k) \\ \mathbf{A}.x(k) & = b(k) \end{cases} \tag{4}$$

with $x(k)$ the vector that is composed of elements of $\Phi(k)$ and $\Delta(k)$, $L_b(k)$ and $U_b(k)$ the boundary vectors, $b(k) \in \mathbb{R}^{\eta \cdot 1}$ the vector that contains the values of $\Delta(k-1)$ of the previous period and the matrix $\mathbf{A} \in \mathbb{R}^{\eta \cdot (\alpha + \eta)}$ that is composed of 0 or 1 following the equation 3 and the structure of the flow graph. It is considered as initial conditions that $d_i(k-1) = 0$ for $i \in [1, \eta]$. The following algorithm 1 is proposed to obtain the sequence of optimal flows Φ by minimizing the criterion $J_V(k)$, n times. In this algorithm, $\Xi \in \mathbb{N}^{\alpha}$ gathers all the indexes of $x(k)$ that correspond to the flow $\phi_a(k)$, and $\Psi \in \mathbb{N}^{\eta}$ the indexes of $x(k)$ that correspond to the capacities $d_i(k)$.

This optimization approach leads to the determination of the optimal sequence of flows. It is well suitable in a deterministic situation when all the flows are supposed to be known. But, the uncontrolled water volumes are often very difficult to determine with accuracy. However, it is possible to estimate their average values based on real measurements as proposed in (Horvàth et al., 2014a), or based on rainfall/runoff models as proposed in (Duviella and Bako, 2012). It will be highlighted that this information will improve the quality of the proposed optimal water management. In the next section, a brief state of the art of predictive rainfall/runoff models is proposed.

Input: $\mathcal{G}$, L_b, U_b, W_i, $\Delta(0)$
Output: Φ

$b(1) = \Delta(0)$

For $i \in 1, n$ do
  Build $\mathbf{A}$ with $\mathcal{G}$
  Build $J_V(i)$
  min $J_V(i)$ such that
  $\begin{cases} L_b(i) \leq x(i) \leq U_b(i) \\ \mathbf{A}.x(i) = b(i) \end{cases}$
  Return $x(i)$

  $\Phi_0(i) = x_j(i)$ with $j \in \Xi$
  $\Delta(i) = x_l(i)$ with $l \in \Psi$
  $b(i+1) = \Delta(i)$
End

Return Φ

Algorithm 1: Optimization algorithm.

3 PREDICTIVE RAINFALL/RUNOFF MODELS

Rainfall/runoff modelling received considerable attention of many researchers over the past two decades. This important attention is motivated by the speed up of the climate change phenomena and their impact on water resources.

The literature can be classified into two approaches according to the a priori knowledge of the system: physical models and data-driven models. The complexity of the considered system is too important and then a physical-based/mathematical model could not be considered because of the huge number of parameters. Moreover, no theoretical hydrological model is able to simulate the behavior of a catchment (Perrin et al., 2003). On the contrary, data-driven, black box fully numerical modelling approaches establish models by using only input and output measurements. Many researchers have developed numerical runoff/rainfall models with varying degrees of success.

Linear models consisting in transfer functions were firstly used due to their simplicity (Young, 1986; Tòth et al., 2007). These methods have been abandoned because of the nonlinearities due to Evapotranspiration phenomenon. Consequently, other approaches have emerged such as the neural networks nonparametric approach (see (Siou et al., 2010) and references therein). However, and despite the acceptable forecasting results, it leads to non-interpretable parameters. In (Bastin et al., 2009), the nonlinearities were represented by a Hammerstein structure using an a priori knowledge of the hydrological system to characterize the static function which also means that the achieved model is non replicable due to the differences between a geographical location and another.

In (Perrin et al., 2003), a daily lumped rainfall/runoff model called GR4J (from the french "Génie Rural 4 paramètres Journaliers") is presented as an improvement of the GR3J (Edijatno and Michel, 1989; Edijatno et al.,) and the performance was tested using five criteria. This lumped model shows to be a reliable tool since it was used in several case studies (Bourgin, 2014; Ficchi, 2017; Dakhlaoui et al., 2017).

More recently, a black box Linear Parameter Varying (LPV) model was investigated for the Rainfall-Runoff Relationship (RRR) in urban drainage networks (Previdi and Lovera, 2009) and rural catchment (Laurain, 2010). This kind of systems consider that a lot of nonlinearities and depend on one or several external variables, called scheduling variables, and then could be linearized at different operating points resulting in a set of local Linear Time-Invariant (LTI) systems. The issue with this approach comes from how to choose the right scheduling variable which is not trivial. In (Previdi and Lovera, 2009), the scheduling variable was chosen as the output of a non parametric model and the model was identified using the least-squares algorithm when the scheduling parameter is taken as the output of the best linear model in (Laurain, 2010) but the optimal identification Simplified Refined Instrument Variable (SRIV) algorithm was applied. Both LPV methods lead to acceptable results. However, in (Duviella and Bako, 2012), the authors proposed an online recursive nonlinear identification algorithm applied to Liane river (France) and was compared to a recursive least-squares linear model over a future horizon of 24 hours. Indeed, the online estimation allows to track the catchment intrinsic variations. The study over a horizon is innovative comparing to the previous cited approaches and shows that even the Fit score (Ljung, 1999) or the Nash coefficient (Nash and Sutcliffe, 1970) are good, the introduction of a prediction horizon deteriorates the estimation results and then increases the number of false alarms and missed alarms.

One of these approaches will be used and probably improved to deal with the prediction of the effects of rainfall on the amount of water that it will be necessary to reject to the sea.

4 CASE STUDY

4.1 Description

The considered case study is based on a real inland navigation network that is located in the north of France. However, the characteristics of the navigation reaches, locks, pumps and gates are realistic but not real. It is composed of three *NR* that are interconnected as it is depicted in Figure 3.a. The NR_1 supplies with a controlled gate and a lock the NR_2. It supplies also with another controlled gate and lock the NR_3. The NR_2 is directly linked to the outlet to the sea, and with a lock to another *NR* that is is not considered. The NR_2 is equipped with a pump downstream that allows rejecting water to the sea. The NR_3 supplies another *NR* that is also not considered in this study.

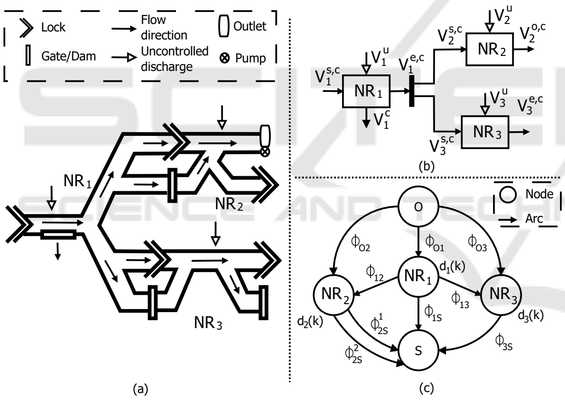

Figure 3: (a) Studied network, (b) the integrated volume model, (c) the flow graph.

The integrated model and the associated flow graph are depicted in Figures 3.b and .c, respectively. The characteristics of the system, *i.e.* dimensions of the *NR* and the boundaries on water levels are given in Table 1.

Table 1: Characteristics of *NR*, with length L in $[km]$, width w in $[m]$, depth l in $[m]$ and upper and lower level boundaries in $[m]$.

	L	w	l	l(+)	l(−)
NR_1	56.724	41.8	3.7	0.1	0.05
NR_2	42.3	52	4.3	0.05	0.05
NR_3	25.694	45.1	3.3	0.05	0.05

The dimensions of the locks, the operating range of the gates and the average values of the uncontrolled discharges are given in Table 2. Notice that the operating range of $Q^c_{dw^2}$ depends on the tide. During low tide, the discharge due to the gravity corresponds to $Q^c_{dw^2} = 30$ $[m^3/s]$. During high tide, this discharge is equal to 0. However, the pump can empty NR_2 with discharge between $[0;40]$ $[m^3/s]$ whatever is the period of the day. That means that the operating range of $Q^c_{dw^2} = [0;70]$ during low tide and $Q^c_{dw^2} = [0;40]$ during high tide. Of course the cost of pumping is higher than the cost of water rejection by gravity. It is the reason of the consideration of two arcs between nodes 2 and S (*see* Figure3.c). The flow $\phi^1_{2,S}$ represents all the water volume that is emptied to the NR_2 with the downstream lock and by gravity to the sea. The flow $\phi^2_{2,S}$ is dedicated to the water volume that is pumped to be rejected to the sea.

Table 2: Characteristics of the lock chamber $\upsilon^{ch}_{\{up;dw\}^i}$ expressed in $10^3.[m^3]$, gates $Q^c_{\{up;dw\}^i}$, controlled and uncontrolled inputs Q^c_i and Q^u_i; discharges are expressed in $[m^3/s]$. X = nonavailable, and $*$ = depends to the operating conditions.

	$\upsilon^{ch}_{up^i}$	$\upsilon^{ch}_{dw^i}$	$Q^c_{up^i}$	$Q^c_{dw^i}$	Q^c_i	Q^u_i
NR_1	6.7	−	X	−	−1	6.56
NR_2	3.5	23	$[0;6.4]$	$[0;*]$	0	0.63
NR_3	5.9	7.3	$[0;30]$	$[0;60]$	0	1.2

By taking into account the tide, the sample time that is considered in these simulations corresponds to $T_M = 6$ hours.

4.2 Design of the Optimal Water Allocation Strategy

The lower and upper bound capacities of the arcs $l_{ij}(k)$ and $u_{ij}(k)$ are determined according to the flow graph $\mathcal{G}$ depicted in Figure 3.*c* and to the known discharge intervals that are given in Table 2 over the period T_M. By considering the case study, the sets are $\chi = \{1\}$, and $\kappa = \{2,3\}$, the number of lock operations is denoted $\beta_{ij}(k) \in \mathbb{N}$ with i the index of the upstream *NR* (i can be the node O) and j the index of the downstream *NR* (j can be the node S):

1. upper bound capacities for arcs $\{\phi_{12}, \phi_{13}, \phi_{O1}, \phi^1_{2S}, \phi_{3S}\}$ are the sum of the maximum available volumes from water intakes over T_M, *i.e.* as an example $V^u_1 = Q^u_1 \cdot T_M$, and volumes that correspond to the lock operations, *i.e.* as an example $\upsilon^{ch}_{up^1} \cdot \beta_{O1}(k)$,
2. upper bound capacities for arcs $\{\phi_{O2}, \phi_{O3}\}$ are the sum of the maximum available volumes from water intakes over T_M, *i.e.* $V^u_2 = Q^u_2 \cdot T_M$ and $V^u_3 = Q^u_3 \cdot T_M$ respectively,

3. upper bound capacity for arc $\{\phi_{1S}\}$, corresponds to the sum of the maximum volumes that can empty NR_1 during T_M, *i.e.* $V_1^c = Q_1^c \cdot T_M$,
4. upper bound capacity for arc $\{\phi_{2S}^2\}$, corresponds to the maximum discharge that can be pumped to the sea during T_M, *i.e.* $Q_2^p \cdot T_M$,
5. lower bound capacities for arcs $\{\phi_{12}, \phi_{13}, \phi_{2S}^1, \phi_{3S}\}$ are the volumes from that lock operations, *i.e.* as an example $\upsilon_{dw^2}^{ch} \cdot \beta_{2S}(k)$,
6. lower bound capacity for arc $\{\phi_{O1}\}$ is the volume from that lock operation and the sum of the maximum available volumes from water intakes over T_M, *i.e.* $\upsilon_{up^1}^{ch} \cdot \beta_{O1}(k)$ and $V_1^u = Q_1^u \cdot T_M$,
7. lower bound capacities for arcs $\{\phi_{O2}, \phi_{O3}, \phi_{2S}^2\}$ are equal to 0,
8. lower bound capacity for the arc $\{\phi_{1S}\}$ is equal to the reserved discharge during period T_M, *i.e.* $V_1^c = Q_1^c \cdot T_M$,

that leads to:

$$\begin{cases} \phi_{O1} \in [\upsilon_{up^1}^{ch} \cdot \beta_{O1}(k) + Q_1^u \cdot T_M;\ \upsilon_{up^1}^{ch} \cdot \beta_{O1}(k) + Q_1^u \cdot T_M], \\ \phi_{O2} \in [Q_2^u \cdot T_M;\ Q_2^u \cdot T_M], \\ \phi_{O3} \in [Q_3^u \cdot T_M;\ Q_3^u \cdot T_M], \\ \phi_{1S} \in [Q_1^c \cdot T_M;\ Q_1^c \cdot T_M], \\ \phi_{2S}^1 \in [\upsilon_{dw^2}^{ch} \cdot \beta_{2S}(k);\ \upsilon_{dw^2}^{ch} \cdot \beta_{2S}(k) + Q_2^{dw} \cdot T_M],\ \ \textit{low tide}, \\ \phi_{2S}^1 \in [\upsilon_{dw^2}^{ch} \cdot \beta_{2S}(k);\ \upsilon_{dw^2}^{ch} \cdot \beta_{2S}(k)],\ \ \textit{high tide}, \\ \phi_{2S}^2 \in [0;\ Q_2^p \cdot T_M], \\ \phi_{3S} \in [\upsilon_{dw^3}^{ch} \cdot \beta_{3S}(k);\ \upsilon_{dw^3}^{ch} \cdot \beta_{3S}(k) + \overline{Q_{dw^3}^c} \cdot T_M], \\ \phi_{12} \in [\upsilon_{up^2}^{ch} \cdot \beta_{12}(k);\ \upsilon_{up^2}^{ch} \cdot \beta_{12}(k) + \overline{Q_{up^2}^c} \cdot T_M], \\ \phi_{13} \in [\upsilon_{up^3}^{ch} \cdot \beta_{13}(k);\ \upsilon_{up^3}^{ch} \cdot \beta_{13}(k) + \overline{Q_{up^3}^c} \cdot T_M], \end{cases} \tag{5}$$

where Q_2^p is the maximum capacity of the pump, T_M is expressed in 10^{-3} s to obtain volumes in $10^3 \cdot [m^3]$, and $\overline{Q}$ the upper value of the controlled discharge interval.

The management objective aims at keeping the capacity objective $D_i = 0$ for each NR. A same and constant quadratic cost function W_i is assigned to each NR_i:

$$W_i((D_i - d_i(k))^2) = \begin{cases} \frac{C_{max}}{(\overline{d_i})^2} \cdot (D_i - d_i(k))^2,\ if\ d_i(k) \leq 0, \\ \frac{C_{max}}{(\underline{d_i})^2} \cdot (D_i - d_i(k))^2,\ if\ d_i(k) > 0, \end{cases} \tag{6}$$

with C_{max} the maximal cost, assuming that $\overline{d_i}$ and $\underline{d_i}$ correspond to the lower and upper boundaries respectively. For the proposed system, $C_{max} = 2,000$ as a big arbitrary value. It is assumed that water volumes that supply or empty the network from natural rivers $\{\phi_{O2}, \phi_{O3}, \phi_{1S}\}$ have less priority than the others $\{\phi_{O1}, \phi_{12}, \phi_{13}, \phi_{2S}^1, \phi_{3S}\}$. Thus, two different costs are chosen such as $\{\omega_{O1}, \omega_{12}, \omega_{13}, \omega_{2S}^1, \omega_{3S}\} = 0$ and $\{\omega_{O2}, \omega_{O3}, \omega_{1S}\} = 1$. Moreover, the cost associated to the pump is defined as $\{\omega_{2S}^2\} = 5$.

Table 3: Navigation demand over 1 week.

Day	1	2	3	4	5	6	7
β_{O1}	21	19	20	22	21	20	0
β_{12}	13	10	14	12	13	14	0
β_{13}	14	12	15	16	13	14	0
β_{2S}	10	9	10	11	9	11	0
β_{3S}	16	15	16	18	16	15	0

4.3 Water Allocation Planning

The proposed water allocation planning algorithm has been implemented in Matlab. A Simulink model has been build to reproduce the dynamics of the studied network. It is run at a discrete time TM corresponding to 6 hours. At each step k, the current states of the NR, *i.e.* $d_i(k)$, the navigation demand and the predicted water volumes that come from rain are taken into account for the minimization of the criterion $J_V(k)$ (*see* equation 4). New setpoints are therefore computed for the controlled devices of the considered network, then a new simulation step is run. The results can be depicted at the end of the simulation.

To test the proposed approach and highlight the requirement of a good prediction of water volumes that come from rain, several scenarios have been built. For all these scenarios, the navigation is allowed during half of the day and then forbidden (12 hours for navigation and 12 hours without navigation). The navigation is also forbidden the 7^{th} day that corresponds to Sunday. The navigation demand is the same for all the scenarios. It is given in Table 3. The effect of the tide is also simulated that allows the rejection of water volume to the sea by gravity during 6 hours during the beginning of the navigation periods and the beginning of the non navigation periods.

The scenarios are built by considering extreme rainy events. They impact directly the inland navigation network by increasing the uncontrolled discharges that supply each NR. These uncontrolled discharges are multiplied by 3 between time 1 to 4 and by more than 4 between time 7 to 14 (*see* Figure 4).

The first scenario (Scenario 1) consists in using the water allocation planning algorithm without any prediction about the increase of the uncontrolled discharges. The NR_1 is the most impacted because the magnitude of uncontrolled discharges is high and the water allocation planning is not able to allocate the water between the NR (*see* Figure 5.a). The rain has also some flood consequence during the second rainy event in the NR_3 (*see* Figure 5.c). However, the volume of the NR_2 stays inside the defined boundaries thanks to the use of the pump (*see* Figure 6.b) and the water rejection to the sea by gravity (*see* Figure 6.a). The water volumes can be rejected by gravity to the

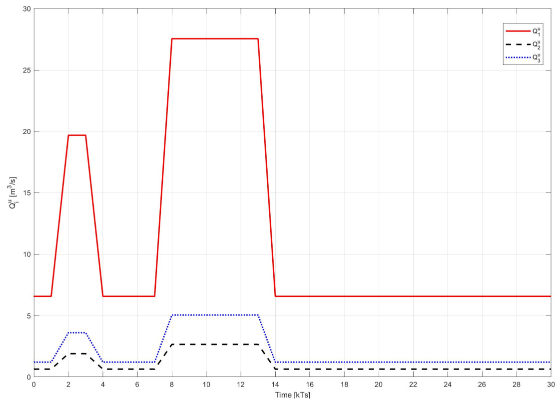

Figure 4: Uncontrolled discharges Q_1^u, Q_2^u and Q_3^u for the defined scenario with two periods of strong rain, where a sample time correspond to 6 hours.

sea only during low tide. The tide is depicted in red dotted line in Figure 6.a. When additional water volumes that come from rain have to be rejected during high tide, it is necessary to use the pump guaranteeing the navigation condition in NR_2 (*see* sample times 4 and 12 in Figure 6.b). This strategy allows limiting the cost due to the use of the pump.

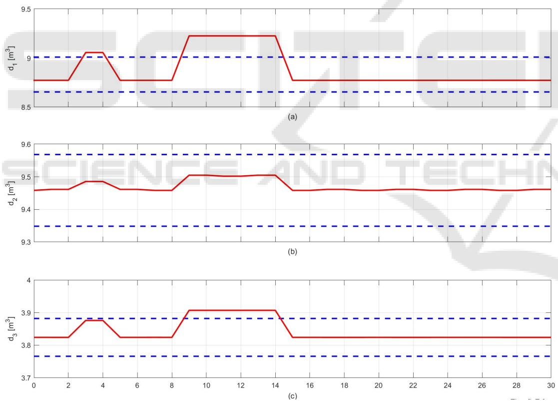

Figure 5: Scenario 1: in red line, the water volume in (a) the NR_1, (b) the NR_2 and (c) the NR_3, in blue dashed line the allowed boundaries.

The second scenario (Scenario 2) is based on the strong assumption that the water volumes from rainy events are perfectly predicted. With this assumption, the three *NR* keep perfectly their navigation objective as it is depicted in Figure 7. In this case also, the pump and the water rejection by gravity are used to keep the objective in the NR_2 by taking into account the tide (*see* Figure 8). The water volumes that are pumped are not so different than the Scenario 1. In this Scenario 2, the water volumes have been better allocated between the three *NR*. This strategy allows limiting the cost due to the use of the pump.

The third scenario (Scenario 3) consists in consi-

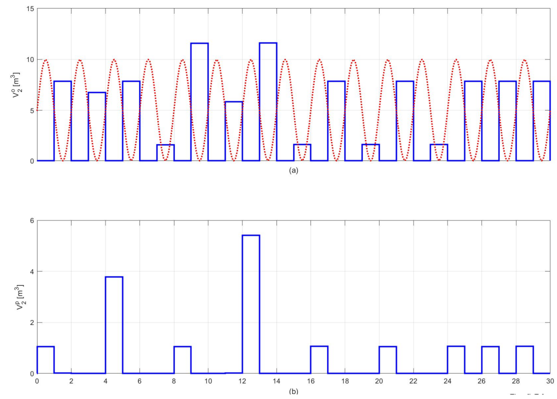

Figure 6: Scenario 1: water volumes that are rejected by (a) gravity to the sea, (b) pump $[m^3]$, with the tide depicted in red dotted line.

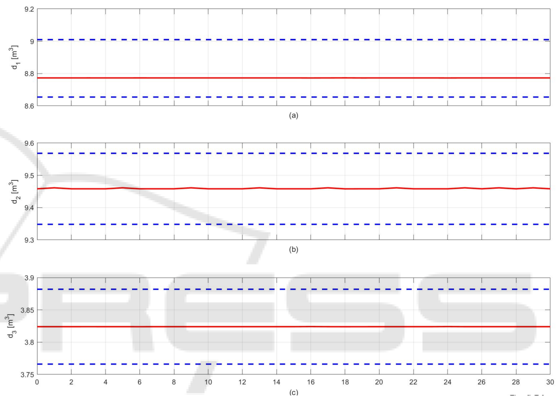

Figure 7: Scenario 2: in red line, the water volume in (a) the NR_1, (b) the NR_2 and (c) the NR_3, in blue dashed line the allowed boundaries.

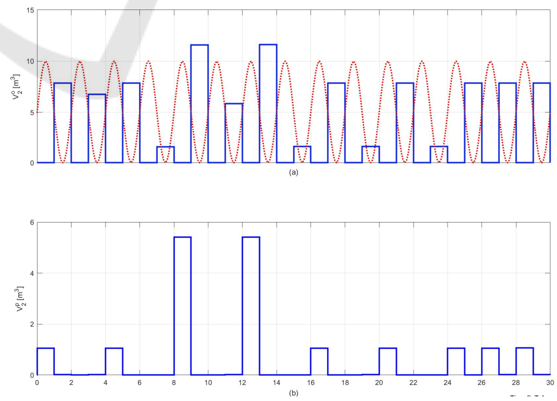

Figure 8: Scenario 2: water volumes that are rejected by (a) gravity to the sea, (b) pump $[m^3]$, with the tide depicted in red dotted line.

dering an error of 30 % in the prediction of the water volumes from rainy events. Based on this assumption, the NR_1 is still the most impacted. However, its volume is kept inside the defined boundaries (*see* Figure

9.a). The objectives are guaranteed also for NR_2 and NR_3 as it is depicted in Figure 9.b and in Figure 9.c. The pump and the water rejection by gravity are still used to keep the objective in the NR_2 by taking into account the tide (*see* Figure 8). The pumped volumes are more progressive during the time, but not so different from the two first scenarios.

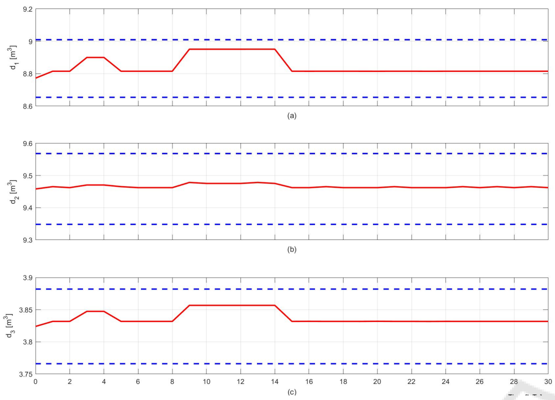

Figure 9: Scenario 3: in red line, the water volume in (a) the NR_1, (b) the NR_2 and (c) the NR_3, in blue dashed line the allowed boundaries.

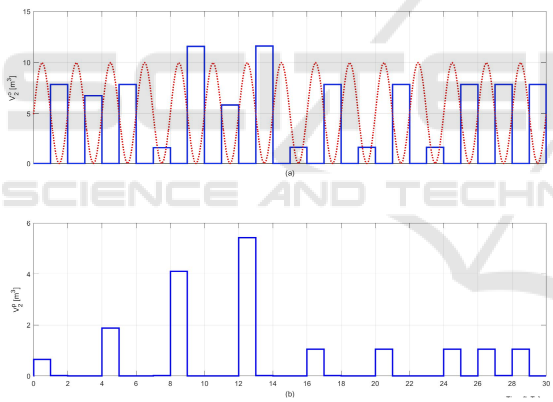

Figure 10: Scenario 3: water volumes that are rejected by (a) gravity to the sea, (b) pump $[m^3]$, with the tide depicted in red dotted line.

The three scenarios show that the prediction of strong rainy events is required to optimize the water resource management of inland navigation networks. However, the Scenario 3 indicates that the management objectives can be kept even if a big error is made on this prediction, *i.e.* an error of 30 %. Hence, a strong effort have to be done on the design of accurate predictive rainfall/runoff models.

5 CONCLUSIONS

In this paper, the integrated model and the flow graph that have been already proposed in past publications, are adapted and improved to deal with the case of inland water systems with outlet to the sea. The water allocation planning algorithm is also adapted to consider these new elements. A realistic case study which characteristics are based on the real inland waterways of the north of France is presented to test these improved tools and algorithm. The simulation results show that the prediction of the impacts of rainy events is necessary to guarantee the management objectives even if an important error in prediction can be allowed. Future works will be dedicated to improve the predictive rainfall/runoff model. Then, the designed tools and methods can be applied on a part of a real inland waterway.

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