# PREVISIONS EN TEMPS REEL DES DEBITS AVEC HYDROMAX : 24 ANNEES D'EXPERIENCE

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Hydromax est l'application utilisée pour prévoir et annoncer les débits de crue (comme les débits d'étiage) de la Meuse et de ses principaux affluents.
Hydromax produit en temps réel des prévisions de débit à court terme basées uniquement sur des mesures de pluie et de débit, et des prévisions de débit à moyen terme utilisant des prévisions météorologiques. Hydromax est opérationnel avec succès depuis vingt-quatre ans. Le but de cette communication est de présenter une description générale des modèles utilisés dans Hydromax et de donner une vue d'ensemble de résultats opérationnels.
La structure du modèle de prévision d'Hydromax comprend trois sous-modèles : un sous-modèle décrivant un réservoir de manière conceptuelle, un sous-modèle statistique de type ARX et un sous-modèle permettant de réaliser des prévisions à moyen terme.
Dans cet article, le fonctionnement d'Hydromax est principalement illustré en utilisant des données expérimentales de la Meuse à la station d'Amay. En particulier, nous abordons la précision des prévisions à courts (8 heures à l'avance) et moyens termes (48 heures à l'avance); le calcul d'intervalles de confiance pour les prévisions; et les informations additionnelles nécessaires au prévisionniste de garde pour réaliser des prévisions fiables.

**MOTS CLEFS :** Modèle ARX, Modèle conceptuel, Prévision, Hydrologie, Crue**.**

## *On-line river flow forecasting with Hydromax:Twenty four years of experience*

Hydromax is the river flow forecasting application for the early warning of extreme hydrological events (floods as well as low waters) in the Meuse river basin and its tributaries.
Hydromax provides in real-time short-term predictions of river flows based on past rainfall and river flow measurements, and long-term river flow forecasting based on weather forecasts. It has been successfully operational for twenty four years. The purpose of this communication is to present a general description of the models used in Hydromax and to give an overview of the operational results.
The Hydromax forecasting model structure involves three submodels: a conceptual reservoir submodel, a statistical ARX prediction submodel and a long-term forecasting submodel.
In this paper, the Hydromax operation is mainly discussed through experimental data from the Meuse River at Amay station. In particular, we address the Hydromax accuracy for short term (8 hours ahead) and long term (48 hours ahead) forecasts; the computation of confidence intervals for the prediction performance; and the additional on-line information to the forecaster on-duty which is needed for reliable forecasts.

**KEY WORDS :** ARX model, Conceptual Model, Forecasts, Hydrology, Flood.

## I INTRODUCTION

The early warning for extreme hydrological events in the Meuse river basin is one of the main missions of the Direction de la Gestion Hydrologique Intégrée of the Walloon Public Administration (SPW). The Meuse River is a navigable river which flows through France, Belgium and the

Netherlands (see Figure 1). The tributaries of the Meuse are notable for their very varied characteristics, with very high flows in winter and extremely low waters in summer.

“Hydromax” is the application that we have developed in collaboration with SPW for river flow forecasting and flood alarms. Hydromax provides in real-time short-term predictions of river flows based on rainfall and past river flow measurements, and long-term river flow forecasting based on weather forecasts. Hydromax has been developed to be user friendly and to fulfill the real-time forecasting requirements. It is now successfully in routine operation for more than twenty four years in the Meuse river basin (Walloon region, Belgium) and its main tributaries. The purpose of this communication is to present a general description of the models used in Hydromax and to give an overview of the operational results. About 230 hydrologic stations scattered in an area of approximately 20000 km² are under permanent on-line monitoring (see Figure 1). The forecasting system is fully operated by SPW. It involves a reliable telemetering network and a data acquisition system able to achieve frequent on-line field measurements of rainfall depths in rain gauges, weather radar data (from the server of the Royal Meteorological Institute (RMI)), water levels and discharges in rivers as well as positions of mobile weirs in navigable rivers. All measurements are stored in a reliable data base with advanced management tools for data reconciliation, data quality control and data exploitation (visualization, warnings and internet access).

In its present state, Hydromax provides on-line river flow forecasting for 35 different stations installed in river basins with areas ranging from 100 to 20140 km². The forecasts are computed with a conceptual/statistical model on the basis of rainfall measurements recorded in the data base from automatic remote sensing of 88 automatic telemetered rain gauges and two weather radars (see Figure 1).

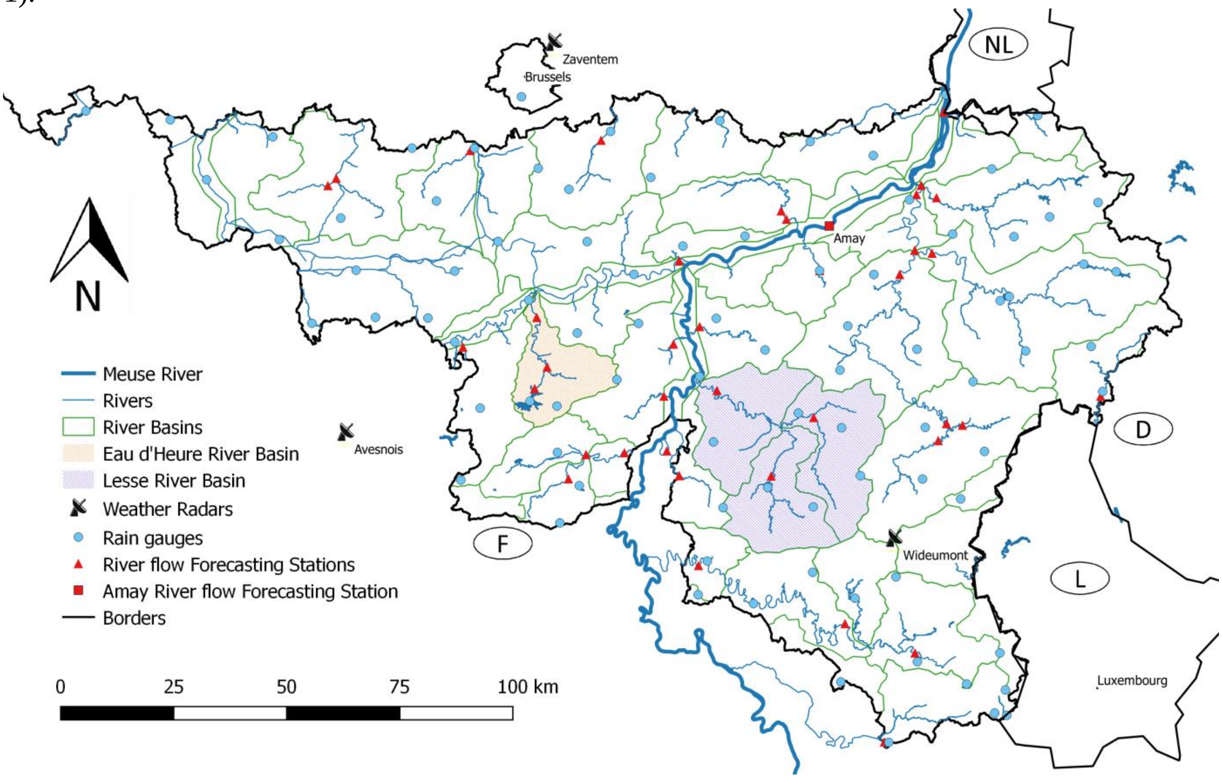


**Figure 1: The Meuse River basin in Wallonia and its main tributaries.**

## II THE HYDROMAX FORECASTING MODELS

In the recent hydrologic literature, three different types of mathematical models are most often considered for river flow forecasting design: mechanistic models, statistical "black-box" models and conceptual models. The Hydromax forecasting model is a combination of the conceptual and the statistical approaches (see Figure 2). The model structure involves three data-based submodels: a conceptual reservoir submodel, a statistical ARX prediction submodel and a long-term forecasting submodel (see Bastin et al. [2009] for details). The data are collected with a basic time-step $\Delta t$ = 1[h]. Hourly rainfall and river flow measurements over a period of several years (including big floods) were available for the identification of the models parameters for each catchment. Obviously, the basic time-step $\Delta t$ must be much smaller than the natural response time for each considered watershed.

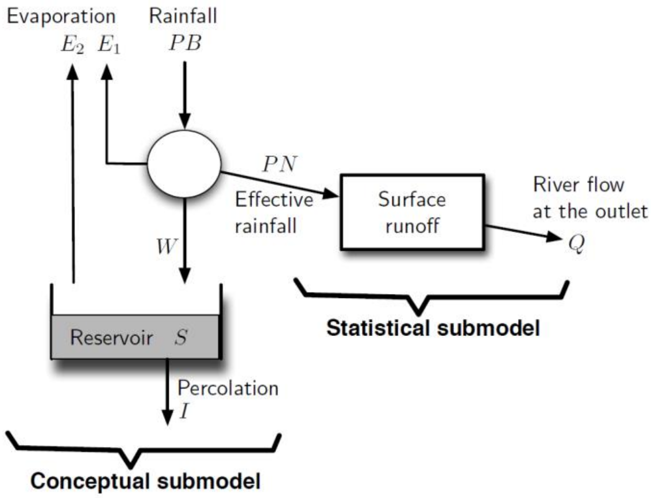


**Figure 2: Structure of the short term forecasting model.**

## II.1 The conceptual reservoir submodel

The input of the model is the mean areal rainfall $PB$ over the considered watershed. It is estimated either from field rain gauges by a Kriging method (see Bastin et al. [1984] for details) or from weather radar images (see Leclercq et al. [2008]). The main task of the reservoir submodel (see Figure 2) is to transform the mean areal rainfall $PB$ into an effective rainfall $PN$ which is supposed to reach the watershed outlet as surface runoff. The model describes the balance of water volumes during each time interval $\Delta t$. During each time interval the amount of precipitated water is decomposed as follows:

$$PB_{(t)} = PN_{(t)} + E1_{(t)} + W_{(t)} \ , \tag{1}$$

with t the discrete time index. $E1_{(t)}$ represents the part of the rainfall $PB_{(t)}$ that directly evaporates during the current time interval. $W_{(t)}$ represents the part of the precipitated water which is stored in the basin under various forms (vegetation interception, superficial depressions, soil moisture). The storage is represented by a nonlinear reservoir with inflow $W_{(t)}$, described by the difference balance equation:

$$S_{(t)} = S_{(t-1)} + W_{(t)} - E2_{(t)} - I_{(t)} \ , \tag{2}$$

where $S_{(t)}$ denotes the stock of the water in the river basin, $I_{(t)}$ is the amount of water drained by percolation and $E2_{(t)}$ is the part of stored water evapotranspirating during the current time interval. The percolation term $I_{(t)}$ is represented by a linear function of the available water stock:

$$I_{(t)} = \alpha(S_{(t-1)} + W_{(t)}) \ , \tag{3}$$

with $\alpha$ a specific percolation parameter. The evapotranspiration terms $E1_{(t)}$ and $E2_{(t)}$ are computed as:

$$E1_{(t)} = \min[PB_{(t)}, ETP_{(t)}] \ , \tag{4}$$

$$E2_{(t)} = \max[0, \min(ETP_{(t)} - PB_{(t)}, S_{(t-1)} + W_{(t)} - I_{(t)})] \ , \tag{5}$$

where $ETP_{(t)}$ is a periodic forcing input of the model which represents an estimate of the seasonal potential evapotranspiration for the considered catchment (see Wery [1990] for details). It is furthermore assumed that there is a physical upper limit $S_{max}$ of the amount of stored water $S_{(t)}$ in the river basin. The water storage term $W_{(t)}$ is then expressed as function of $S_{(t)}$ and $PB_{(t)}$ in order to:

- guarantee the condition $0 \leq S_{(t)} \leq S_{max}$ $\forall t$;
- verify the hydrological principle that effective rainfall $PN_{(t)}$ increases with both rainfall intesisty $PB_{(t)}$ and water stock $S_{(t)}$.

The following function (proposed in Lorent and Gevers [1974]) satisfies these requirements:

$$W_{(t)} = [S_{max} - S_{(t)}]\left[1 - exp\left(-\beta \frac{PB_{(t)} - E1_{(t)}}{S_{max} - S_{(t)}}\right)\right] \ , \tag{6}$$

with β a specific runoff parameter. The conceptual submodel thus involves three positive parameters ($S_{max}, \alpha, \beta$) which are calibrated for each considered watershed. In addition, we must have $0 \leq \beta \leq 1$ in order to guarantee $PN_{(t)} \geq 0$.

### II.2 Statisitical ARX prediction submodel

At each time step t, a forecast $\widehat{Q}_{(t+H)}$ is computed for the future time instant (t+H) (where H is the short-term prediction horizon of H measurement time steps) as a linear combination of past river flow measurements and past effective rainfall values, with a linear regression model (ARX model) of the form:

$$\widehat{Q}_{(t+H)} = \sum_{i=1}^{n} a_i \, Q_{(t-(i-1)H)} \ + \ \sum_{j=1}^{m} b_j \, PN_{(t-(j-1)H)} \ , \tag{7}$$

where $Q_{(t-(i-1)H)}$ denotes the river flow measurement at the past time instants (t-(i-1)H) while $PN_{(t-(j-1)H)}$ represents the effective rainfall cumulated over H successive time steps and computed with the conceptual submodel. For each catchment, the values of the coefficients $a_i$ and $b_j$ are determined from experimental data by linear regression. To get accurate forecasts, the prediction horizon H has to be obviously smaller than the natural response time of the river basin. As a rule of thumb, it is selected between the one fifth and the one third of the peak time of the unit hydrograph. The dimensions *n* and *m* of the regression terms in the model are selected using classical statistical tools of system identification theory (correlogram of prediction errors, Bayesian Information Criterion, see e.g. Ljung [1999]) according to a parsimony principle.

### II.3 Long term forecasting submodel

The goal here is to compute river flow forecasts over prediction horizons which are larger than the natural response time of the river basin. This requires using the future rainfalls from the meteorological forecasts. Such long-term river flow forecasts are computed by iterating the short-term prediction model as:

$$\begin{aligned}\widehat{Q}_{(t+kH)} &= \sum_{i=1}^{k-1} (a_i \, \widehat{Q}_{(t+(i-1)H)} + \ b_i \, \widehat{PN}_{(t+(i-1)H)}) \\ &\quad + \sum_{j=k}^{n} a_j \, Q_{(t-(j-1)H)} \ + \ \sum_{j=k}^{m} b_j \, PN_{(t-(j-1)H)} \ ,\end{aligned} \tag{8}$$

where $\widehat{Q}_{(t+(i-1)H)}$ are successive iterated river flow forecasts and $\widehat{PN}_{(t+(i-1)H)}$ are effective rainfall forecasts to be provided by the user.

### II.4 Upstream river flow as an additional input

In some instances, the presence of major hydraulic infrastructures may significantly influence the river flow rates so that simple rainfall-runoff models may become ineffective. A typical example is when the outflow of a large storage dam controlled by human operator may disturb the river flow independently of the rainfall. In Wallonia, this situation occurs in the Eau d'Heure River as illustrated in Figure 1. In that case, the statistical ARX prediction submodel is augmented with an additional input as follows:

$$\widehat{Q}_{(t+H)} = \sum_{i=1}^{n} a_i \, Q_{(t-(i-1)H)} \ + \ \sum_{j=1}^{m} b_j \, PN_{(t-(j-1)H)} \ + \sum_{l=1}^{p} c_l \, Q_{in_{(t-(l-1)H)}} \ , \tag{9}$$

where $Q_{in_{(t-(l-1)H)}}$ denotes the upstream dam outflow at the past time instants.

## III HYDROMAX OPERATIONAL RESULTS

Hydromax is in routine operation in the Meuse River basin since 1994. In its present state, Hydromax provides on-line river flow forecasting for 35 catchments with areas ranging from 100 to 20000 [km²]. The forecasts are computed with the above presented models on the basis of hourly rainfall measurements recorded in 88 telemetered rain gauges and two weather radars (see Figure 1).

The use of Hydromax for on-line river flow forecasting is illustrated in Figure 3 for the Lesse River at Gendron station on February 9, 2016. The geometry of the Lesse river basin can be visualized in Figure 1. In Figure 3, the blue curve represents the actual discharge evolution during the six days before the 9th at 7 PM. The blue bars in the bottom subplot represent the average total rainfall PB. On the basis of these data, Hydromax first computes the effective rainfall PN with the conceptual reservoir submodel:

$$PN_{(t)} = PB_{(t)} - E1_{(t)} - W_{(t)} \,, \qquad (10)$$

with $E1_{(t)}$ and $W_{(t)}$ given by expressions (4) and (6) respectively. In Figure 3, the effective rainfall PN is represented in cyan in the bottom subplot. Then, Hydromax computes a short term forecast 6 hours in advance (i.e. H = 6 [h]), with the ARX prediction submodel (7), which is represented by the big blue dot in Figure 3. Remark that the forecast warns the user that the flow rate could reach the pre-alarm threshold. Afterwards, Hydromax computes two long term forecasts. The first one, represented as a red curve, is a pessimistic forecast based on hypothetical future rainfalls (red vertical bars in the bottom subplot) that are rather intensive (16 [mm] in 12 [h]). Now, remark that this forecast warns the users that the alarm threshold could be reached within the next 24 hours. The second long term forecast (green curve) is the most optimistic one since it assumes that the rainfall stops instantaneously. It can be seen that, even in this case, the pre-alarm threshold will be exceeded for about 12 [h].

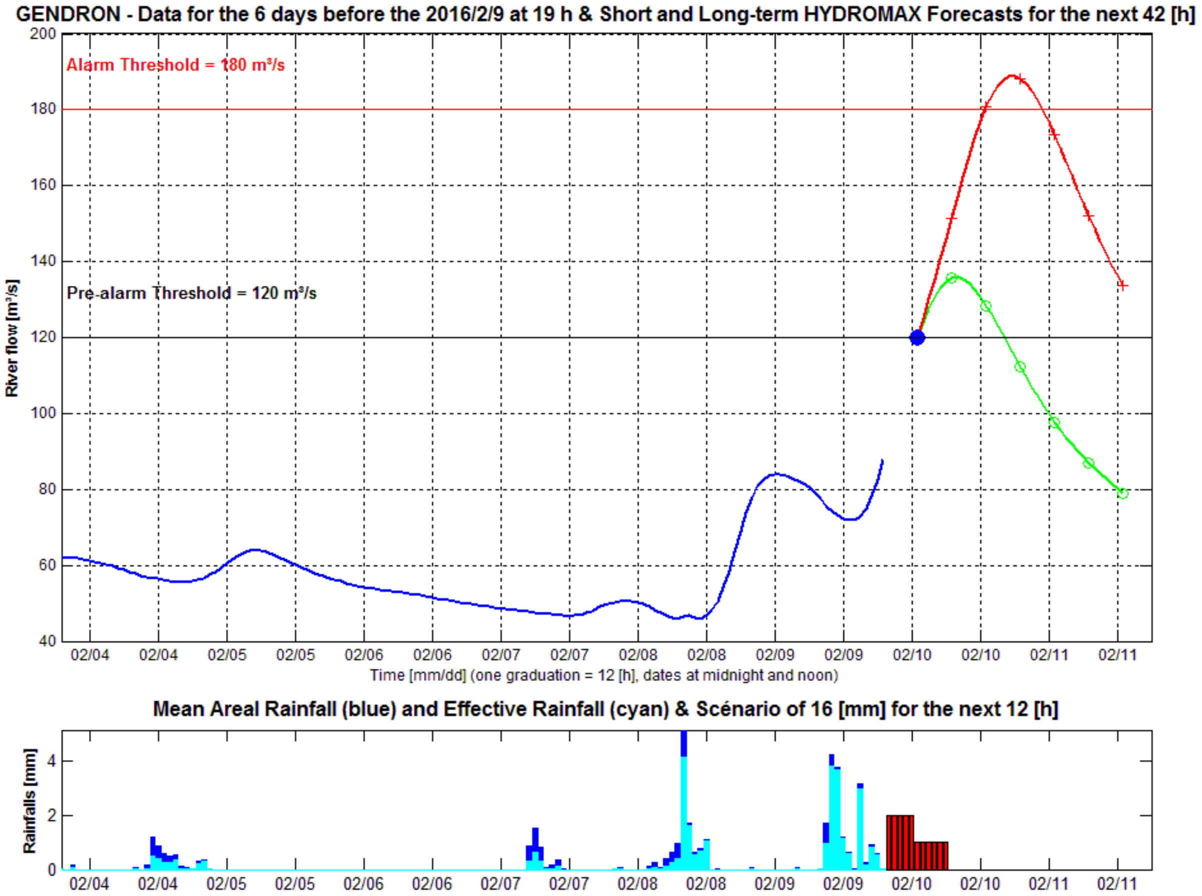


**Figure 3: Short and long-term forecasts for the next 42 hours after February 9 at 7 PM, 2016 at Gendron Station on the Lesse River.**

In Figure 4, for the period from the 8th of February 2016 to the 12th of February 2016, the blue solid curve represents the measured river flow rate, while the green dots represent a set of 6 [h] ahead short-term forecasts issued from Hydromax. The short-term forecast obtained at Figure 3 is indicated in Figure 4 by an arrow. Remark that the actual river flow which was a posteriori observed at this station is in good agreement with the long-term forecasts curves obtained at Figure 3. Furthermore, it can be seen that the pre-alarm threshold as well as the peak of the flood are predicted with a good accuracy.

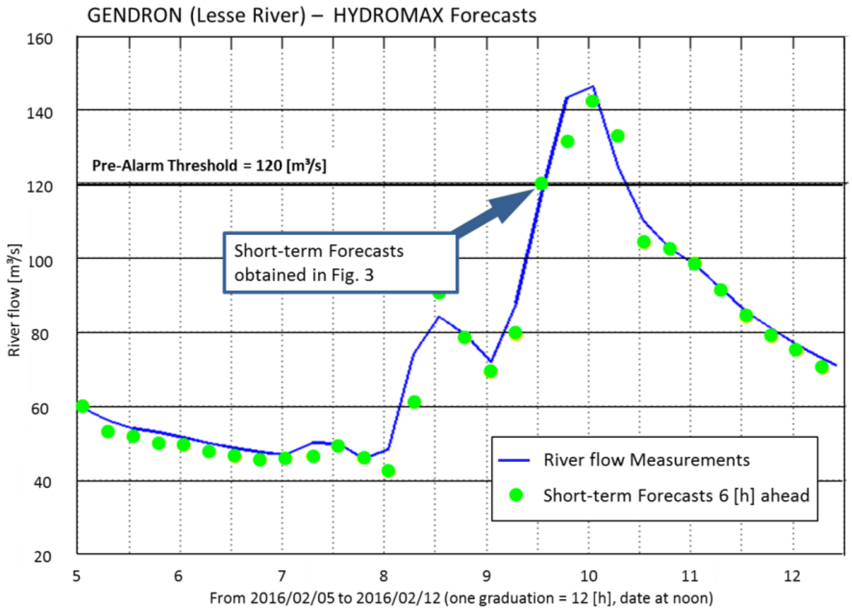


**Figure 4: Short-term forecasts at Gendron Station on the Lesse River from the 5th of February 2016 to the 12th of February 2016.**

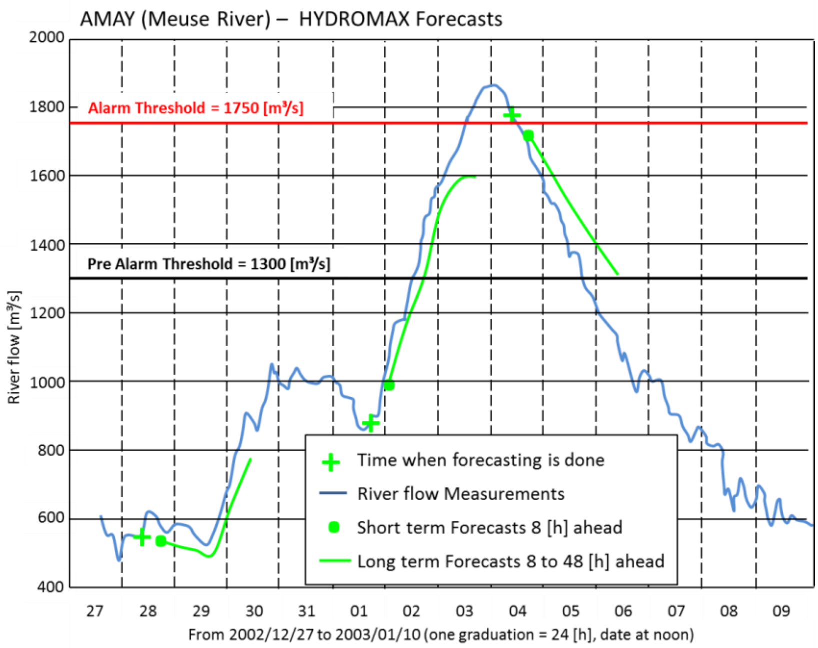


**Figure 5: Short and long-term forecasts at Amay Station on the Meuse River during the big flood, from the 24th of December 2002 to the 10th of January 2003.**

With Hydromax it is also possible to analyze the efficiency of long-term forecasts. Figure 5 represents three short and long terms forecasts for Amay station on the Meuse River (see Figure 1) during a big flood conditions. The two first ones are before the flood peak and the last one 12 hours after. For this station, the short term horizon (H) is 8 hours and the long term is 48 hours. The blue curve is the measurement of discharges for a period of about 14 days from December 27, 2002 to the January 9,

2003. The crosses are the time instants when forecasting in done, the green dots are the short-term forecasts and the green curves are long term forecasts.

## IV PERFORMANCE AND CONFIDENCE INTERVALS

For the analysis of the performance of the conceptual reservoir submodel, the reader is referred to the paper Bastin et al. [2009] (Section 3, Figure 3). In this paper, experimental results are analyzed in details for the period 2001 to 2003 characterized by two extreme floods. This analysis especially emphasizes the efficiency of the computation of the effective rainfall *PN(t)* whose production appears well correlated with the occurrence of high flow rates and big floods.

Here, the performance of Hydromax forecasting is illustrated in Figure 6 with the example of Amay station on the Meuse River. In this figure, the statistics of the experimental relative prediction errors for the short-term forecasting (computed with equation (7)) are represented as a function of the predicted discharge. This graph is obtained by using more than 140 000 short-term forecasts (about 18 years of past data, from 1995 to 2013).

The underestimated and the overestimated forecasts are considered separately. The 5 % extreme values are eliminated to obtain the experimental blue dots in Figure 6 corresponding to the 95 percentile limits, computed with a 10 m³/s moving window. A red spline shown in Figure 6 is then fitted to these experimental data.

The performance of long-term forecasts (48[h]), based on the same experimental data and computed with equation (8), is then shown in Figure 7, in comparison to the short-term forecasts.

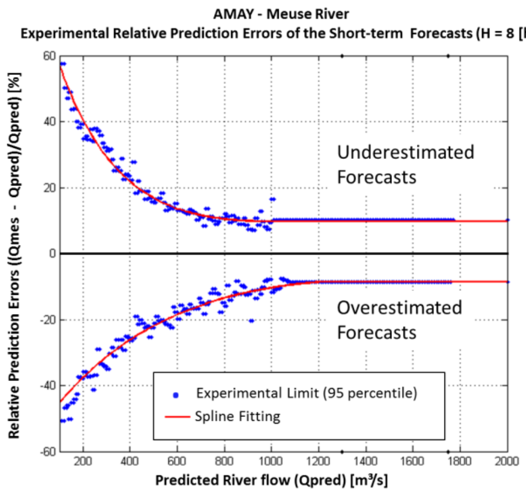


**Figure 6: Experimental 95 percentile limits of relative prediction errors for the short term forecasts (H = 8 [h]) at Amay station based on 16 years of forecasting.**

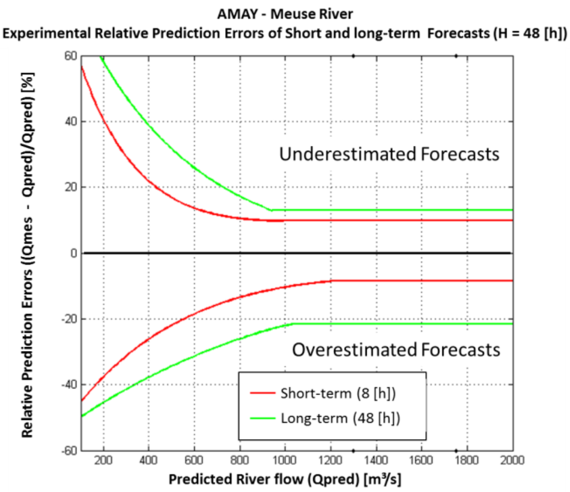


**Figure 7: Smoothed 95 percentile limits of relative prediction errors for the short-term (H = 8 [h]) and long-term forecasts (H = 48 [h]) at Amay station based on 16 years of forecasting.**

The statistics of the experimental prediction errors, as represented in Figures 6 and 7 can obviously be directly used to define confidence intervals for the forecasting. The use of confidence intervals is of special interest for navigable rivers such as the Meuse River where the natural riverbed has been transformed such that the water flows through successive pools separated by weirs. In addition, many weirs are equipped with a hydropower plant located in a by-pass channel. Weirs and hydropower plants are disturbance sources which can have high impacts on the river flow. For instance, at Amay station, on the Meuse River (see Figure 1), the river flow is a combination of the upstream Meuse and Sambre River discharges which can be disturbed by thirteen weirs and seven hydropower plants.

The various sources of random disturbances produce river flows which are highly volatile as it can be seen in Figure 8 (see section V). In order to deal with this volatility, Hydromax forecasts are provided with confidence intervals that are also shown in Figure 8. In this figure, it can be seen that, whatever the future rainfall scenario is, all the forecasts are almost the same, with confidence intervals having amplitude of the same order of magnitude than the flow measurements volatility.

Another example corresponding to higher flow rates is given in Figure 9. In this case, the optimistic and the pessimistic long-term forecasting curves, as well as the confidence intervals, are clearly distinct, and the probability to exceed the pre-alarm threshold is very high.

## V ADDITIONAL INFORMATION FOR THE FORECASTER

In this section, we comment on the additional information given in Figure 8 and Figure 9. As Hydromax is directly connected to the field through the hydrological data base and with the RMI server (for the precipitation measurements by weather radars and the rainfall forecasting models), it is possible to provide fully automatic on line river flow forecasts. It is however important to notice that the final publication of the forecasts is always done under the control of a (human) forecaster who has to be careful because the system may sometimes provide forecasts that are misleading if the data used for the prediction are incidentally unreliable. In such case, the forecaster may have to correct the forecasts, on the basis of his own empirical experience, before their publication.

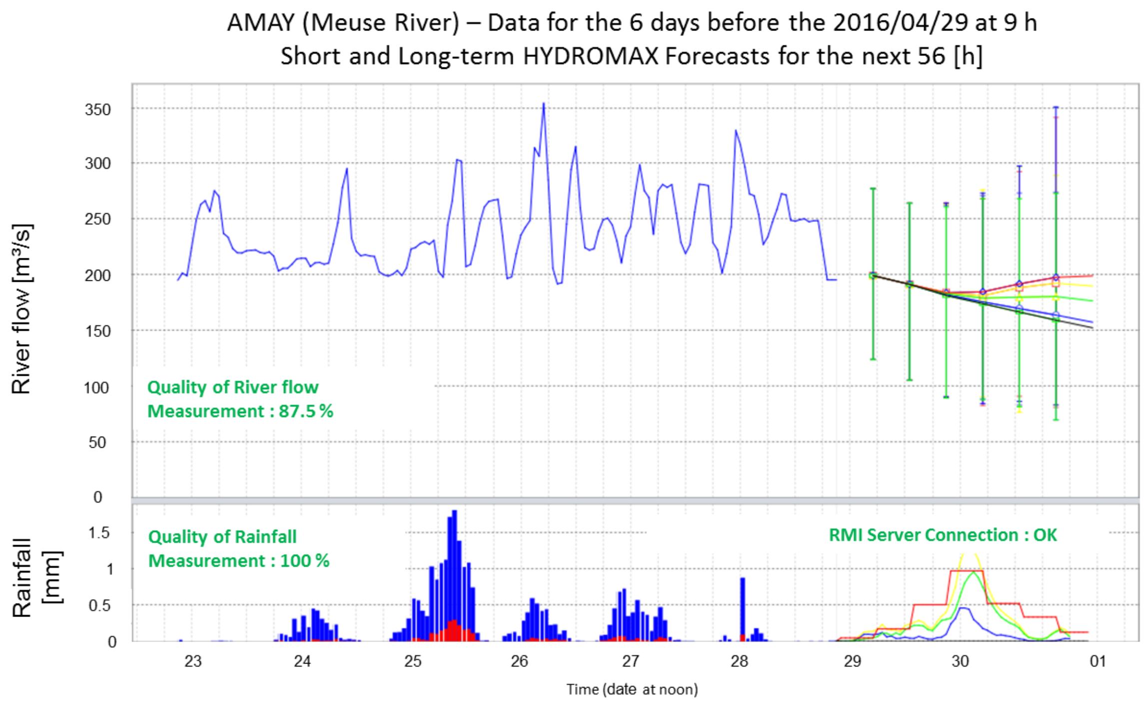


**Figure 8: Forecasts at Amay station. Graph with confidence intervals and additional information for the forecaster.**

In order to help the forecaster on-duty in this task, all of the rainfall and river flow data are checked to give information about their quality. Missing and unreliable data (e.g. outliers) are discarded and replaced by interpolated or extrapolated values. Moreover quality coefficients, corresponding to the percentage of the reliable data within the set of data that are needed to achieve a forecasting, are displayed. For example, in Figure 8, it can be seen that the quality coefficient for the river flow is 87.5 % because the last measurements were not available at the forecasting time and thus extrapolated. In addition, as it is illustrated in Figure 9, the user is informed when the RMI rainfall forecasts are missing.

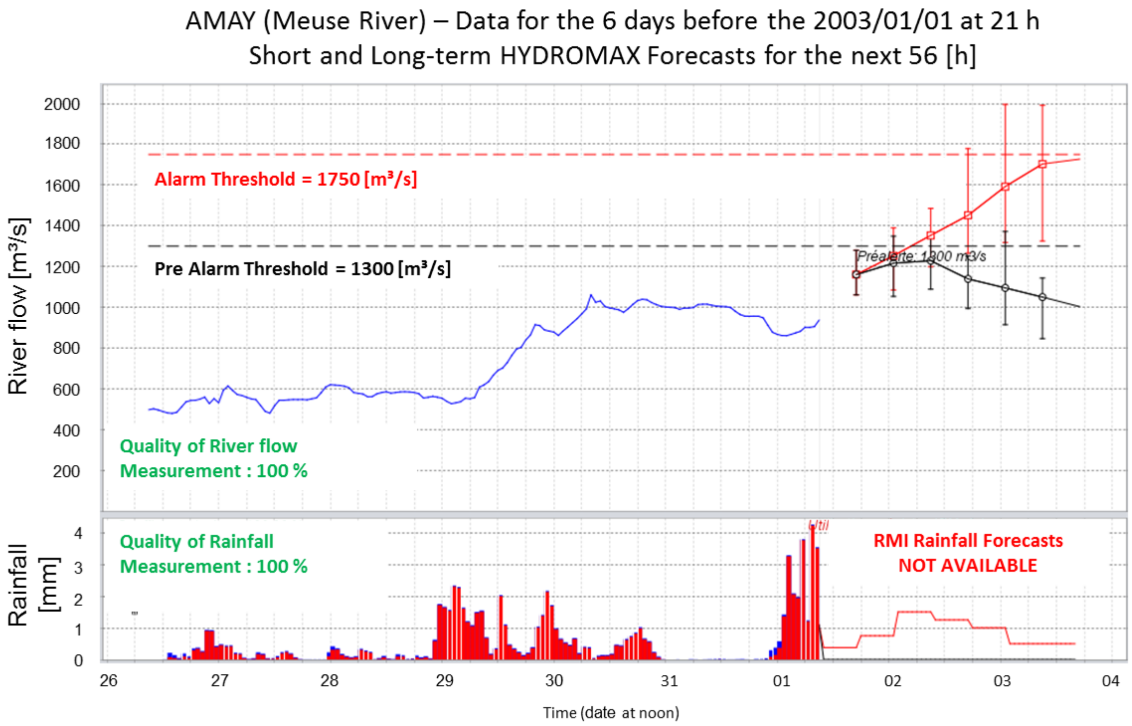


**Figure 9: Forecasts at Amay station in high flow conditions. Graph with confidence intervals and additional information for the forecaster.**

## VI CONCLUSIONS

In October 1994, the first version of Hydromax was developed in the SPW operational center for the flood forecasting. From the beginning, this application has been used by people working directly on the field. So the design and development choices of Hydromax were always made to meet the operational requirements. This is one of the keys of Hydromax success.

An important advantage of Hydromax is the economy of data. The only data sets which are needed are the rainfall on the basin and the flow in the river. The physical description of the watershed is not required. Moreover, the models are systematically validated on floods which are not used for model identification so that the identified parameters remain valid from a flood to another.

Nowadays, the Hydromax application runs in a web environment as a fully integrated tool in SPW and provides, every hour, new river flow forecasts for 35 stations on natural as well as navigable rivers. With these forecasting facilities, the « SPW Direction de la Gestion Hydrologique Intégrée » may then provide relevant information to the Crisis Centre of the Walloon Region in order to ensure the setup of emergency aid, the advertisement of local public administrations and the diffusion in the media.

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