1. Introduction

According to the statistics in recent decades, floods represent almost 40% of natural disasters in the world [6], and most of these flood are caused by rivers overflow. This issue is very challenging for governments in terms of on-time prevention. Many solutions used to face flood are usually built for developed countries, and are not well suited for African countries because of geographical and climatological differences. Concerning developing countries, mainly in Africa, a high number of victims and damages observed could be explain by these reasons :

– low data accuracy of numeric weather prediction to have good flood forecast quality,

– lack of meteorological information in many regions that makes the flood forecasting difficult,

– Low forecast accuracy of FFS

Concerning the first two problems, we proposed two solutions in [2] and [3]. It is important to say that the resolution of NWP data accuracy does not necessary resolve the FFS forecast accuracy since the data accuracy is one of the FFS accuracy problem but not the only problem. The goal of this work is to resolve the third problem, by adding auto-adaptability to FFS and reducing the inaccuracy of forecast. In this respect, we target the main output hydraulics model parameters of FFS such as river's level forecast assuming that they are the source of flood forecast inaccuracy when there are environmental changes. In others words, we suppose that the forecast system is working correctly and if ever an inaccuracy is observed in the forecast results, then, one of the main reasons are linked to the hydraulics models that provides output river's level. The problem are then probably caused by environmental changes over space or time.

The main contribution of this paper is the proposition of an adjustment module that gives the auto-adaptiveness ability to FFS. Basically, we developed an algorithm that uses past forecast and observed data to assess the error in the future FFS forecast and correct the forecast. The observed data are collected from sensor networks.

The rest of the document is organized as follows : Section II presents hydraulic flood forecasting systems features. The scope of this work is given in Section III. In Section IV, the adjustment algorithm designed to improve auto-adaptiveness is presented. Section V provides a discussion on the evaluation of the proposed algorithm. Conclusion and future directions ended this work.

2. FFS based on Hydraulic models

FFS predict the upcoming of flood in a certain delay. According to [11], advances in flood forecasting have been slackened by the ability to assess rainfall continuously over space. According to [2] FFS can be categorized into two groups : the sensors-based systems [8, 10, 13, 1, 9, 7] and hydraulic models based systems [15, 14, 12]. In the remaining of this section, we aim to portray FFS based on hydraulic models.

Medium and long term flood warning system are more required for densely populated areas in order to give enough time for reducing damages. To predict medium or long term flood, they rely on both Numeric weather prediction(NWP) and Hydraulic Models. Like the forecasting of weather where models are used to simulate atmosphere behavior, hydraulic models can be used to simulate rivers behavior based on rain forecast in order to estimate whether a flood may occur.

2.1. How FFS based on hydraulic models work ?

FFS based on hydraulic models usually need recalibration and updates when they are used in a region other than the one for which they were designed for (eg. a FFS built in Europe can not properly work in Africa without some recalibration process). In fact, NWP data are received from meteorological stations and other data like topography, vegetation, and so on are collected from other systems such as GIS (Geographical Information Systems). The entire data are sent to the Hydraulic model. The output of the hydraulic model is then used by FFS to evaluate flood risk. This output could be for example, the river's level or river's flow.

2.2. The problems of FFS based on Hydraulics models

FFS based on hydraulic models are able to predict water levels at any location in the modeled area for a given date if ever the NWP data are available. According to [4] one of World's best practice in FFS incorporates hydraulics models and data assimilation. Nevertheless there are some problem that we can observed in these FFS :

– Existing FFS are built for specifics region, and it could have some inaccuracy problem if these FFS are installed to another regions because of environmental differences. So Existing FFS need to be updated and re-calibrated if we want to use them in some other regions. This recalibration task are not usually easy and in certain cases, it is needed to rebuild the hydraulic model used in the FFS.

– There are some important parameters in the environment which are able to change over time and which are not taken into account. So if the environment meet some changes, existing FFS will not consider these changes, and this situation could seriously affect FFS forecast accuracy.

We realized that this type of systems has a main problem : auto-adaptiveness regarding environmental and regions changes. Our target here is to build a module which is able to give auto-adaptiveness ability to FFS in order to increase forecast accuracy. The next section presents the proposed solution.

3. Auto-adaptiveness ability of FFS based on hydraulics models

The main challenge here is to improve the coherence of hydraulic model forecast data when environment parameters are changed or have involved. We consider that as much as hydraulic model are auto-adaptive regarding a given region, the system will be geographically portable. To get our goal, we rely on a basic hydraulic model described above to propose a new approach.

3.1. Auto-adaptiveness hydraulic FFS

We leverage the basic model presented before by including others modules. Basically, observed data are collected from sensors network and they are used with forecast data produced by the hydraulic model, in the system to realize the adjustment task. These forecast and observed data are used as input in a learning program in charge of errors prediction.

An error is the difference between a prediction P(t) at a time t and the observation Obs(t) at a time t as shown in (1).

$$error(t) = P(t) - Obs(t) \tag{1}$$

The learning program uses a set of past errors, to make the future error prediction. After, the learning program sends the predicted error to the adjustment program, which applies the required update (Figure1) before output of the new adjusted forecast.

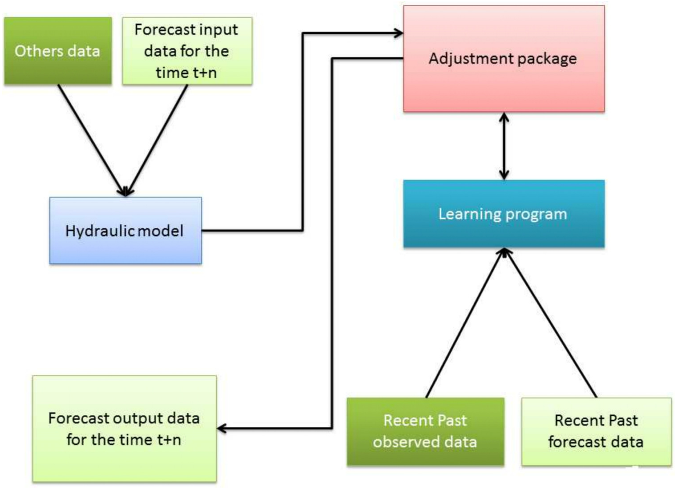

Figure 1 : Proposed hydraulic FFS architecture

3.2. Adjustment module description

3.2.1. Basic concepts

We consider a sensor network as a set of sensors at the risk zone that collect real-time data. Thus, the system collects forecast data from hydraulic model and observed data collected from sensors network installed across the river. A learning program evaluates error between forecast and observed data. When a new input forecast data is received, the adjustment program relies on the learning program to adjust them regarding future predicted error. These data are afterwards used by the system to evaluate flood risk.

3.2.2. Adjustment formalization

The learning program uses the function (2) to make prediction of the future error using past errors. Function (2) is a basic exponential smoothing [5] method of time series data used to make short term predictions. In this paper, forecast and observed data, are daily data.

$$\varepsilon(t) = \alpha * e(t) + (1 - \alpha) * \varepsilon(t-1) \tag{2}$$

where

– **e(t)** represents the error (1) measured between a prediction and an observation at the time **(t)**

– $\varepsilon(t)$ represents the prediction of the error at a time **(t)**

– α represents the auto-adaptiveness speed. $\alpha \epsilon [0; 1]$

Regarding (2), if $\varepsilon(t-1) > 0$ it will means that the prediction P(t) made by the FFS will be greater than the waiting observation Obs(t), so to adjust the predicted value P(t), we need to apply $A(t) = P(t) - \varepsilon(t-1)$ and consider A(t) instead of P(t).

But if in other hand, $\varepsilon(t-1) < 0$ it will means that the prediction P(t) made by the FFS will be lesser than the waiting observation Obs(t), so to adjust the predicted value P(t), we need to apply $A(t) = P(t) + |\varepsilon(t-1)|$

Based on the two formulations above we can define (3) as a general expression of the adjustment equation.

$$A(t+1) = P(t+1) - \alpha * e(t) - (1-\alpha) * \varepsilon(t-1) \tag{3}$$

where :

– **P(t+1)** is the prediction received from the hydraulic model at a time **(t+1)**

– ε**(t-1)** represents the prediction of the error at a time **(t-1)**

– **A(t+1)** represents the adjusted prediction value at the time **(t+1)**

The role of algorithm 1 is to evaluate the error after each prediction regarding to the observations. Obs(t) is the collected value at time t sent by a sensor. Algorithm 2 aims to adjust the prediction received from hydraulic model according to a predicted error.

Data: New observation data Obs(t)
Result: evaluated error e(t) between P(t) and Obs(t)
while *New observation Obs(t) is received* **do**
    – e(t)=P(t)-Obs(t)
    – Save (t, e(t))
end

Algorithm 1: Error evaluation

Data: New prediction data P(t)
Result: Adjusted value A(t) of the prediction
initialization (α);
while *New prediction P(t) is received* **do**
    – Predict the potential error on the prediction received using (2)
    if *($\varepsilon(t-1)$ >0)* **then**
        A(t)=P(t)-$\varepsilon(t-1)$;
        Save (t, P(t), A(t));
        Use A(t) instead of P(t) for the flood alert evaluation;
    else
        A(t)=P(t)+$\varepsilon(t-1)$;
        Save (t, P(t), A(t));
        Use A(t) instead of P(t) for the flood alert evaluation;
    end
end

Algorithm 2: Data adjustment

4. Adjustment algorithm validation

4.1. Data sets

To evaluate our adjustment module, we used measured groundwater level data collected daily during 1 hydraulic year in a small town in Senegal and we also used groundwater forecast data made by an hydraulic model for the region during the same time.

4.2. Scope of the test

The scope of this test is to show how the algorithm uses past errors made between the forecast data and observation data, to adjust the future forecast data in the aim of reducing the difference between hydraulic prediction and real observation even if the model is not suitable for the zone.

We want to remind that if we used a model which is not suitable for the region, it is to materialize the fact that the environment has changed or the model has been taken to another regions instead of the region where it was designed. So if the model is in another region or if the environment of the model has changed, it will be not suitable for the new condition and will need recalibration. We want to show by this simulation how the adjustment module can reduce the inaccuracy of the model due to these changes.

In others words, this test shows how, if an hydraulic model designed and calibrated for a given region is taken to another region, the forecast error done by the hydraulic model in the new region will be adjusted gradually until the system reach to a stable mode where the error between prevision of the hydraulic model and the observation realized on the groundwater will be minimized.

4.3. Experimentation

This part presents the evaluation method and the different tools used to validate the algorithm efficiency. To implement and run our solution, we used a MySql database, and the python language.

4.3.1. Evaluation

To characterize the efficiency of our algorithm, let us consider δ, the accuracy indicator defined in (4).

$$\delta = \frac{1}{N} \sum_{i=0, Y_i \neq 0}^{N-1} \mid \frac{Y_i - X_i}{Y_i} \mid \tag{4}$$

where Y represents observed value, X the forecast value and N the number of data observed.

4.4. Result and discussions

Figure 2 presents the measured data collected, the forecast data provided by the hydraulic model and the data provided by hydraulic model coupled with the adjustment module. All these data are for a period of approximatively 1 year for the same region. According to this figure, it can be observed that the difference between forecast of the hydraulic model and the observation is significant, as the accuracy indicator for forecast data is δ=0.08. This difference between the hydraulic model and the observation could be explained by the fact that the hydraulics model was not suitable for the zone and needed to be calibrated to work well. This situation could illustrate the potential behavior of an hydraulic model when the initial environment has changed.

It can be also observed that the difference between forecast of the hydraulic model coupled with adjustment module and the observation is very low, as the accuracy indicator for the hydraulic model coupled with the adjustment module is δ=0.003 which is largely smaller than the accuracy indicator of the hydraulic model alone (0.003 over 0.08). This low difference between the hydraulic model coupled with adjustment module and the observation could be explained by the auto-adaptiveness behavior that the adjustment module gives to the hydraulic model. At each time the adjustment module tries to anticipate the error on the future forecast and use it to adjust the prediction received from the hydraulic model.

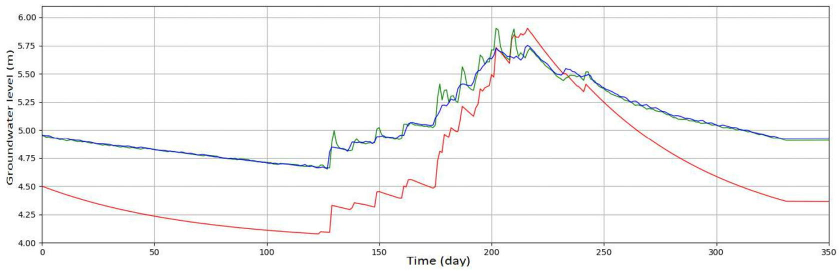

Figure 2 : Forecast realized by (hydraulic model + adjustment module) in Green, Observations in Blue and Forecast realized by model without adjustment module in red

This figure portrays in a very simple way the efficacy of the adjustment module in the improvement of the forecast capacity of the hydraulic Model. The difference between the two models materialized by the different values of δ shows that the adjustment module has a great impact on the forecast, over 96.25% of accuracy improvement. However, some fluctuations can be observed at the beginning of each regime. This is because at each time the adjustment module tries to adapt itself to the new regime and if the regime is changing continuously over the time the fluctuation will continue, because the module will always try to adapt itself to the new regime.

5. Conclusion

We presented a module which is able to improve the forecast quality of hydraulic models when the model is not suitable or well calibrated for a given region. The results obtained show that this module improves the accuracy of forecast data and can play a significant role in the improvement of the auto-adaptiveness of flood forecasting systems capacity. For future works, we plan to propose a module that manages the integration of observed and forecast data collected from sensor networks and meteorological stations.

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