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A New Generation, GIS Based, Open Flood Forecasting System

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Abstract: This paper describes the development of a new generation flood forecast system based on an open interface approach. The system, "MIKE FLOODWATCH", is implemented in the ArcGIS environment utilising a variation of the ArcHydro geodatabase. The system can be linked directly to a range of telemetry and other hydrological databases which permits the seamless import and pre-processing of real time measurements, including rainfall radar and other grid-based data. The open interface allows the system to be coupled to virtually any hydrological or hydraulic model in order to obtain predictions of water levels and flows in the model domain. An advanced forecast dissemination module is capable of automatically posting forecasts via inter/intranets, SMS text, e-mail or fax. Complementing this system is the development of a new data assimilation module for the MIKE 11 hydrodynamic model. The module utilizes an efficient updating technique to improve the model state through a feedback process to match the available observations prior to the time of forecast and to automatically correct the model predictions into the forecast period. The system has recently been commissioned for the Flanders government in the Scheldt estuary in northern Belgium.

Keywords: Floods, real-time forecasting, GIS

1. INTRODUCTION

Accurate and reliable flow forecasting forms an important basis for efficient real-time river management, including flood control, flood warning, reservoir operation and river regulation. In order to achieve this objective, it has become a common practice to apply GIS based software that integrates data management and forecast modelling tools in a single environment known as a data management and forecast modelling shell. Such shells incorporate the ability to configure links to telemetry, manage and examine real-time data, register forecast modelling tools, carry out manual or scheduled forecast simulations, examine the results and publish selected data to a range of media; including web, fax, e-mail and SMS for mobile phones. Moreover, the systems can be used to carry out scenario analyses to provide early flood warnings, flood alleviation and other.

Complementing the forecast modelling shell are the forecast modelling tools used to compute e.g. a flood forecasts. The core of state-of-the-art operational flow forecasting systems is a hydrological/hydrodynamic simulation model that uses information of the current state of the river basin together with forecasts of the model forcing (precipitation, evapotranspiration and hydraulic model boundaries) to provide forecasts of the water levels and discharges in the river system. The forecast errors of such a system are related to errors in the current state of the river basin initialised by the simulation model, errors in the model forcing forecasts and errors related to the simulation model itself (such as model structural errors and use of non-optimal model parameters). In order to improve the estimate of the initial state of the system and to reduce the simulation errors in the forecast period a data assimilation procedure is often implemented in the forecast system. In general, data assimilation (often denoted model updating in hydrological applications) is a feedback process where the model prediction is conditioned to the observations of the river system (typically water levels and discharge measurements).

The combination of a resilient and robust forecast modelling shell and a forecast model tool that incorporates an accurate and fast updating technique constitutes a strong tool that can be used by flood managers to provide vital, sometimes life saving, information to local authorities and the vulnerable populace.

The paper is outlined as follows: In Section 2 a description is given of a new forecast modelling shell that integrates data management and forecast modelling methodologies in a GIS environment. The system is known as MIKE FLOODWATCH (DHI, 2000). In Section, 3 a new, fully adaptive error forecast technique is described, which has been incorporated into a data assimilation framework in MIKE 11 (Hartnack and Madsen, 2001; Madsen et al., 2003) and in Section 4 the forecast technique is applied in a real-time flood forecasting application in the Scheldt estuary in northern Belgium. Conclusions are given in Sections 5.

2. INTEGRATED DATA MANAGEMENT AND FORECAST MODELLING SHELL

Based on the concept for the existing MIKE FLOODWATCH, which has been applied in numerous projects world-wide, DHI Water & Environment has developed a new, modern and extremely robust forecast modelling shell with the objective to integrate data management, forecast models and dissemination methodologies in a single system.

The system, which is based on the common water resources relational database for management and storage of data, is fully integrated into ArcMap GIS 8.3 from ESRI, hence taking advantage of the newest GIS technology available on the market including modern scripting facilities and fast and robust methods for visualisation and processing of geographical data.

Real-time data including meteorological forecasts, radar imagery and telemetry data can be imported into the database and used e.g. as input to hydrologic and hydraulic forecasting models. Real-time data imported from external sources is quality assured according to user-defined quality criteria and stored in the system database.

In order to ensure a high level of openness and flexibility, the forecasting shell system makes consistent use of the EUROTAS industry file format for model interfacing. The systems may be used to execute any model type including meteorological weather models, hydrologic models, hydraulic and hydrodynamic models, advection-dispersion models, water quality models, forecasting models, error forecast models and others. Alternatively, models from other suppliers may be registered with MIKE FLOODWATCH and run within this environment.

System tasks such as import of real-time data from remote data acquisition stations, execution of forecast modelling tasks or dissemination of selected results to relevant parties (Figure 1) are handled consistently using a task scheduler that facilitates definition of the above tasks as well as common system tasks such as database maintenance and deletion of old instances of forecast modelling tasks, log messages etc.

Access restrictions can be defined for each user or group of users, hence making it possible to ensure that only suitably qualified and experienced staff can gain access to the parts of the system that require particular know-how. In turn, this adds to the philosophy of offering an extremely robust system that can operate in a range of user environments.

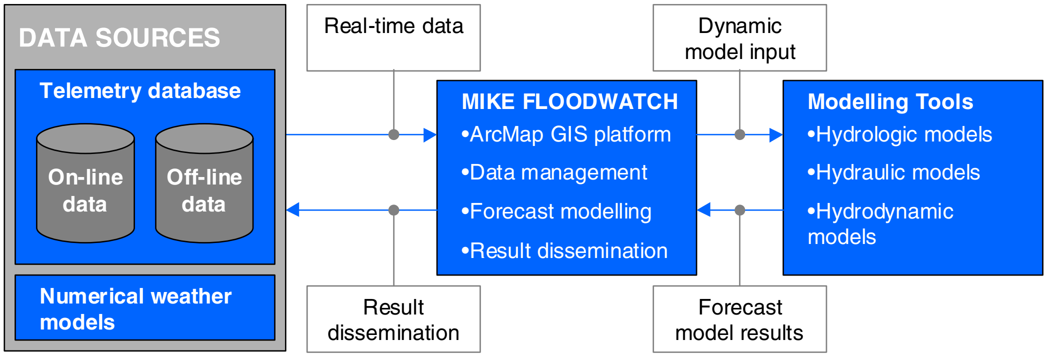

Figure 1 – MIKE FloodWatch links telemetry to models and automatically runs forecast operations

3. ADAPTIVE ERROR FORECAST METHOD

In this section a new, hybrid data assimilation procedure is presented that has been implemented in the MIKE 11 flood forecasting system developed at DHI Water and Environment (DHI, 2003). MIKE 11 is a comprehensive, one-dimensional modelling system for the simulation of flows, water quality and sediment transport in rivers and other water bodies (Havnø et al., 1995; DHI, 2003). The MIKE 11 system integrates different computational modules for the basic process descriptions such as hydrology, hydrodynamics, advection-dispersion etc. For flood forecasting applications the MIKE 11 hydrodynamic and rainfall-runoff modules are adopted.

Previous real time updating routines in MIKE 11 have relied upon a unique relation existing between water level and discharge at the updating point. The system analysed the deficit or excess of discharge compared to observations and applied corrective lateral inflows at the update points. The system has proved reliable in the past but suffered from two main drawbacks. Firstly, it could not be applied in areas affected by tides or backwater. Secondly, the process was iterative, requiring complete model simulation iterations in situations where two or more updating points were located along a single river reach.

To circumvent these inadequacies, a new general filtering framework has been developed for data assimilation. The new updating procedure in the filter is a succession of two steps. First, the model is employed to issue a one-time-step ahead forecast, following which the observed data are assimilated with the forecast to provide an updated state. The assimilation step is a linear combination of the data and the model in which the forecast error at the measurement point (denoted the innovation) is distributed to the entire model state using specified weighting functions. The formulation of the weighting functions is the most critical part of the filtering scheme, and different schemes mainly differ from each other in the way the gains are calculated. The most comprehensive linear assimilation scheme is the Kalman filter whereby the gains are determined based on a minimisation of the expected error of the updated state vector in terms of the errors of both model dynamics and data. In this case the weighting functions or Kalman gains are determined sequentially based on the dynamical evolution of the forecast covariance matrix of the state vector

In MIKE 11 the ensemble Kalman filter has been implemented (Hartnack and Madsen, 2001; Madsen et al., 2003). Experiences with the filter shows that the computational requirements for obtaining a proper representation of the covariance matrix are of the order of 100 model runs, which is often too computationally expensive in real-time applications. In this work, a very cost-effective filtering procedure has been developed based on predefined gain vectors that are assumed constant in time. In this case the filtering update is only slightly more expensive than a normal model run. Three different gain functions are assumed; a constant, a triangular, and a mixed exponential distribution as shown in Figure 2.

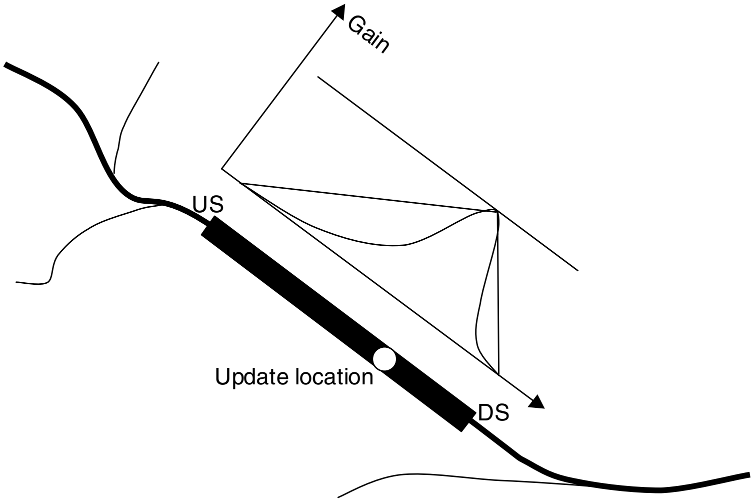

Figure 2 - Definition of Gain Function for a Measurement (Update) Location

The amplitude of the gain function at the measurement location should reflect the confidence of the observation as compared to the model forecast; that is, if the amplitude is equal to unity the measurement is assumed to be perfect, whereas for smaller amplitudes less emphasis is put on the measurement as compared to the model forecast. The distribution and the bounds of the gain function should reflect the correlation between the model forecast error at the measurement location and the errors at nearby grid points. In this work an amplitude of one is used.

The filtering procedure described above can be applied to update the state of the river system up to the time of forecast. Within MIKE 11, the filter can be applied at both discharge and water level points.This updated state can then be used as initial conditions for a model forecast. In this case, however, the forecast skills of the model will be limited to a time horizon where the initial conditions are washed out. To keep the model on the "right track" for a longer period the filtering procedure is combined with error forecasts at the measurement points. The principle of this combined approach is illustrated in Figure 3. At each update time step in the filtering period (prior to the time of forecast), the model innovation is acquired at all update locations. For each update location this gives rise to a time series of innovations that covers the filtering period up to the time of forecast (or the time of the last measurement). At the end of the filtering period, an error forecast model defined at each update location is then used to propagate the innovation in the forecasting period and update the affected state variables accordingly using the filtering algorithm. In real-time the error forecast models are applied at each measurement location from the time of the last observation to the end of the forecast period. Thus, the forecast methodology is insensitive to missing data; a situation which is commonly encountered in operational forecasting. In addition, the new module does not require additional model iterations, thereby reducing the time required to generate a forecast.

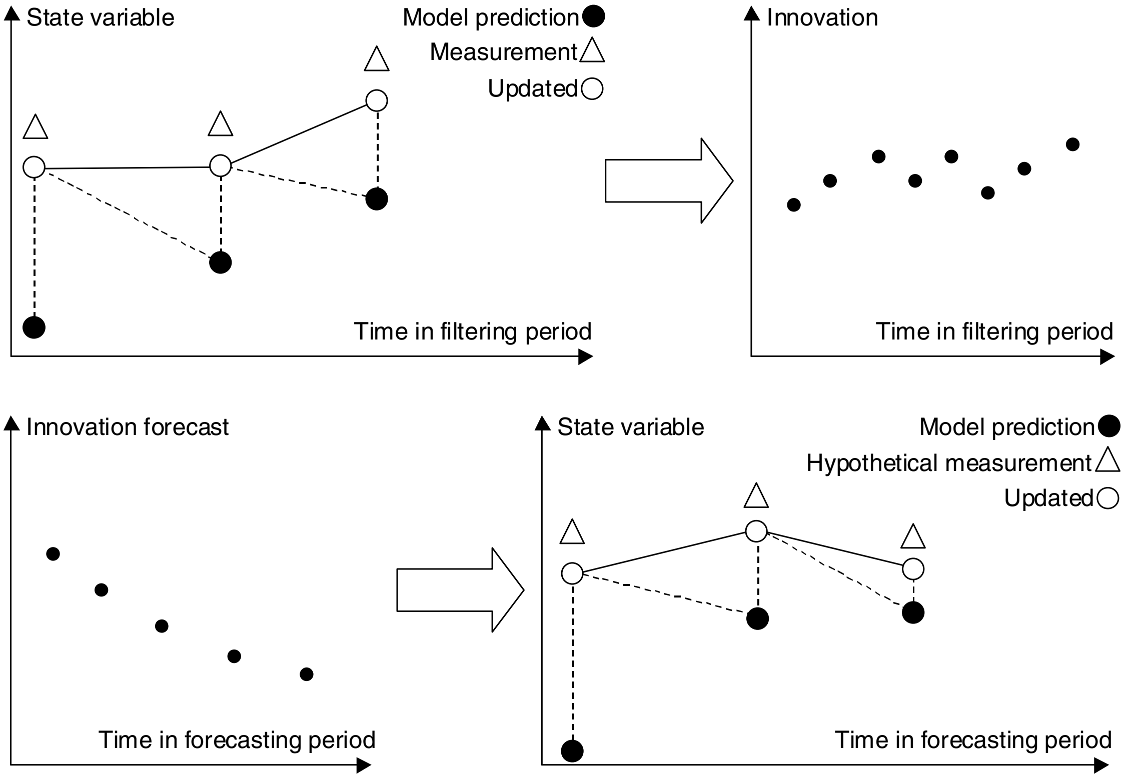

Figure 3 - Illustration of the Combined Filtering and Error Forecast Procedure

The error forecast model can be defined as a general linear or non-linear model with a one-step ahead prediction that depends on the previous errors or innovations, model states and model forcings. In order to ensure a fast, accurate and objective derivation of the error forecast models, fully automatic parameter estimation techniques have been incorporated. On the basis of a user-defined time window in the filtering period prior to the time of forecast, the parameters of the error forecast model are estimated. The error forecast models are updated when a new forecast is to be issued using time series of the most recent data. This allows the error forecast models to adapt from one forecast to the next based on the physical conditions prevailing at the time of forecast without any need for calibration or user intervention in general. In the case of a linear error forecast model, the model parameters are estimated using least squares regression techniques. In the case of a non-linear model, the shuffled complex evolution (SCE) algorithm (Duan et al., 1992) is applied for the parameter optimisation.

4. FORECAST APPLICATION IN NORTHERN BELGIUM

The new updating technique as incorporated into MIKE 11 was used jointly with the forecast modelling shell, MIKE FLOODWATCH, to provide real-time forecasts of river stage and discharge at selected locations throughout the Scheldt estuary in Northern Belgium. The study area covers an area of more than 6500 km^2; including the major cities Brussels and Antwerp, ref. Figures 4 and 5. More than 40 catchments were identified in the study area, each of which was modelled using the NAM rainfall-runoff model to produce lateral inflows (both surface and subsurface flow) to the major rivers traversing the catchments.

The hydraulic model includes more than 500 km of rivers that meet with the Scheldt River, the mouth of which is located in the tidally affected estuary that adjoins the North Sea. More than 140 weirs and culverts have been included in the model to describe accurately the energy loss across structures and associated backwater effects. The model is resolved using approximately 8000 grid points (water level and discharge) and runs at a constant time step of 2 minutes. In the upstream part of the hydraulic model, which is not affected by the tide, updating is accomplished using a first order auto-regressive model, whereas in the downstream tidal area, the model innovations are known to exhibit a structured, harmonic behaviour, which justifies the use of the following biharmonic error forecast equation:

$$E_i = a+b*cos(2*pi/(12.4/24)*t)+c*sin(2*pi/(12.4/24)*t)+d*cos(2*pi/(25.8/24)*t)+e*sin(2*pi/(25.8/24)*t) \qquad (1)$$

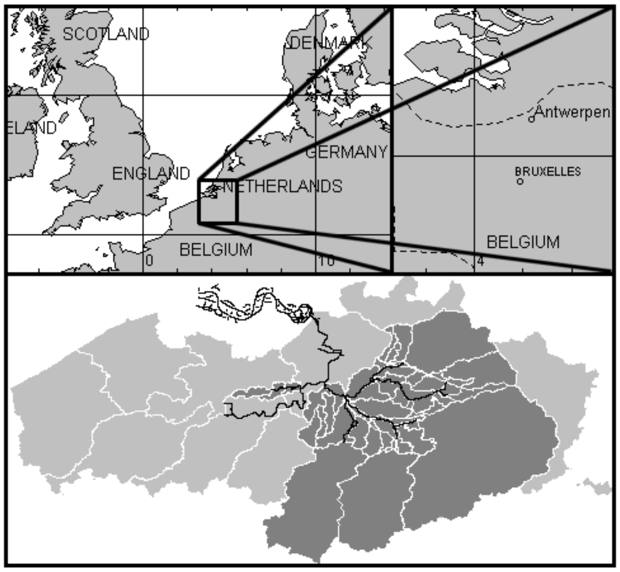

Figure 4 – Location of the Scheldt Esturary in Belgium showing model extent

in which E_i is the forecasted model error at the ith time level, a, b, c, d and e are coefficients to be estimated and t denotes time. For both measurement locations updating is accomplished using a triangular gain distribution with amplitude of one. Consequently, model updates will match the observations at the update locations in the filtering period prior to the time of forecast (or to the time of the last measurement).

The feasible parameter space of the estimated parameters is shown in Table 1. Moreover, the table shows a single instance of the estimated parameter set at Schelle-409 – a highly tidal update point located south of the city of Antwerp, just downstream of the confluence of the Scheldt and Rupel rivers. For the case shown in the table, the forecasting model was run using a simulation period of 14-01-2004 12:00:00 to 18-01-2004 12:00:00 with the time of the forecast set to 16-01-2004 12:00:00. Consequently, the model was used to provide a 48 hour forecast. For the purpose of testing the ability of the updating method to recover from erroneous model forcings or measurement errors in general, a shift was introduced at the downstream model boundary to reflect the effect of a storm surge in the Scheldt estuary.

Parameter	Lower limit	Upper limit	Estimated
a [m]	-10	10	0.48378
b [m]	-5	5	0.25484
c [m]	-5	5	-0.16949
d [m]	-5	5	0.01513
e [m]	-5	5	-0.00005

Table 1 Feasible parameter space for the biharmonic error forecast model.

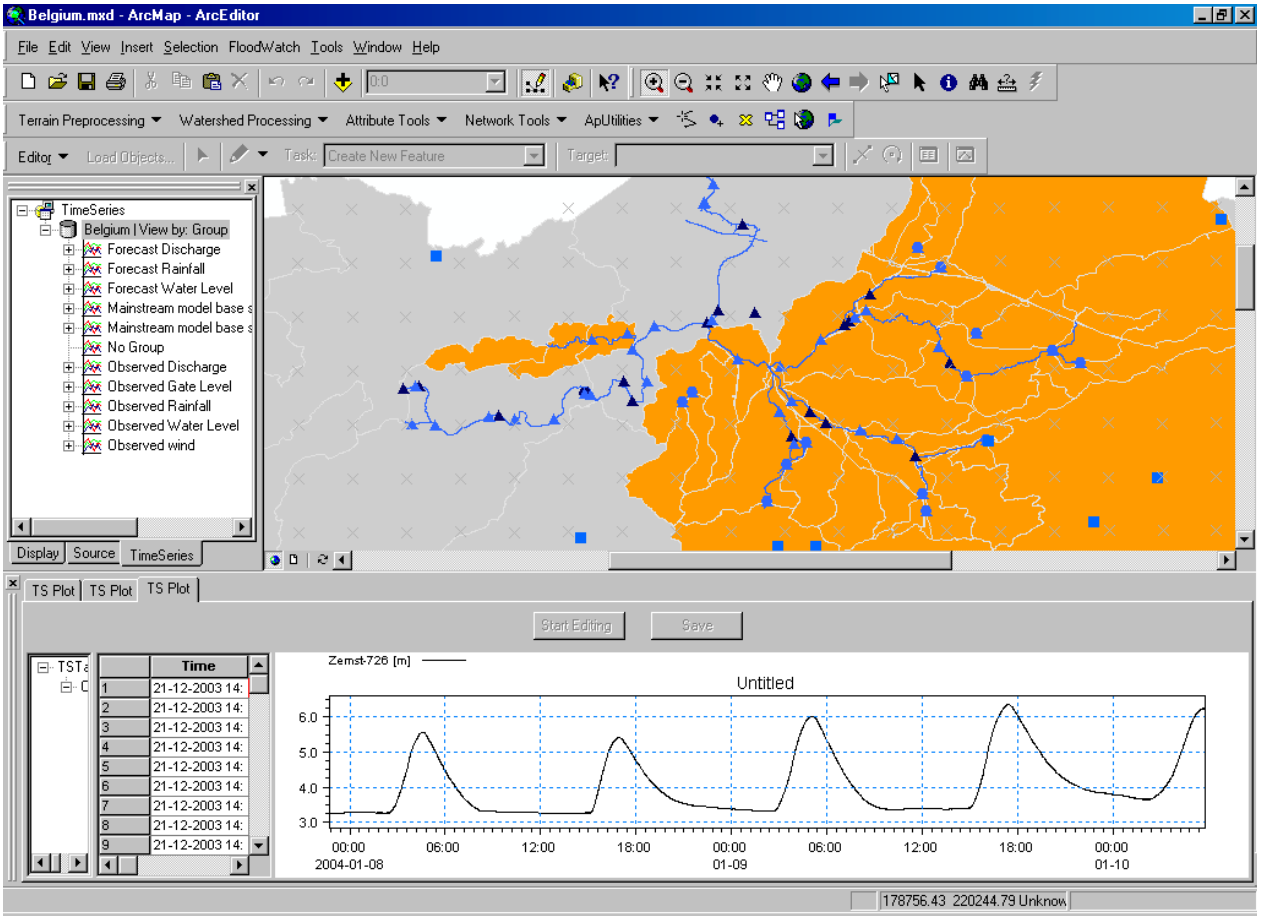

Figure 5 – Layout of the On-Line Data Management and Modelling System in the ArcMap GIS Environment

Figure 6 shows the measured and forecasted water levels at Schelle-409 with and without state updating. It is noted that the measurements consist of both valid data and missing data. Consequently, the example demonstrates that the updating method handles missing data - a feature that is useful in a real-time environment. In the case where updating is applied, the simulated water level is identical to the measured water level up to the time of the forecast. At the time of the forecast, or more generally, at the time of the last measurement, the parameters of the error forecast model are estimated automatically, (Table 1), using the optimisation algorithm described in Section 3. In the forecasting period, i.e. after 16-01-2004 12:00:00, the forecasted model innovation is applied in the filtering scheme to produce a water level forecast that is significantly improved as compared with the situation where state updating is excluded.

In order to illustrate the concept of error forecasting, the observed and estimated model innovations at Schelle-409 are shown in Figure 7. Approximately 24 hours of acquired model innovations were used to optimise the parameters of the biharmonic error forecast equation (1), hence making it possible to estimate the model error in the forecasting period.

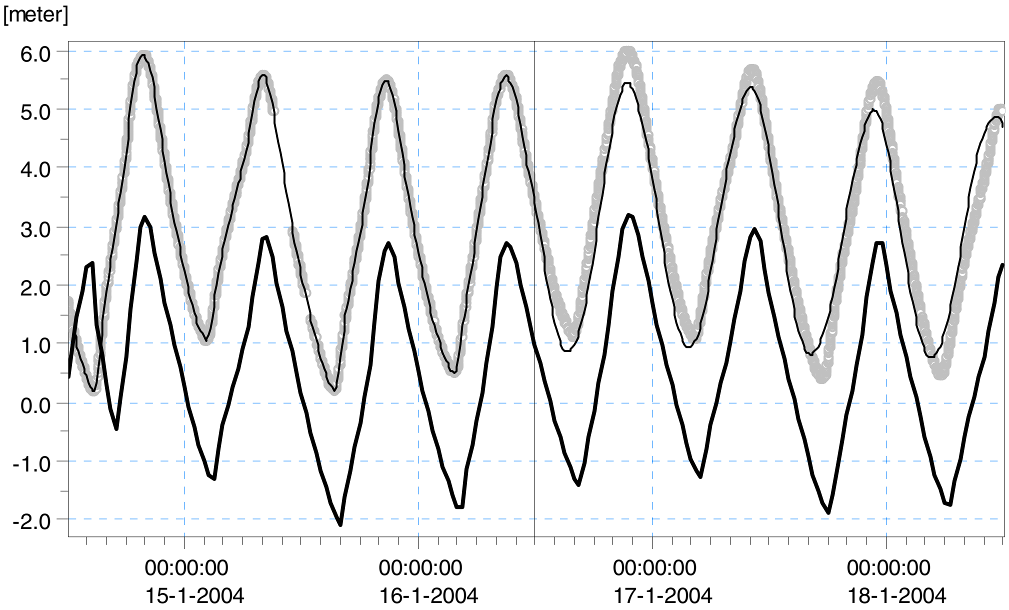

Figure 6 – Measured (○) and Forecasted (-) water level at Schelle-409 both with updating (thin line) and without updating (thick line). The time of forecast is at 16-01-2004 12:00:00

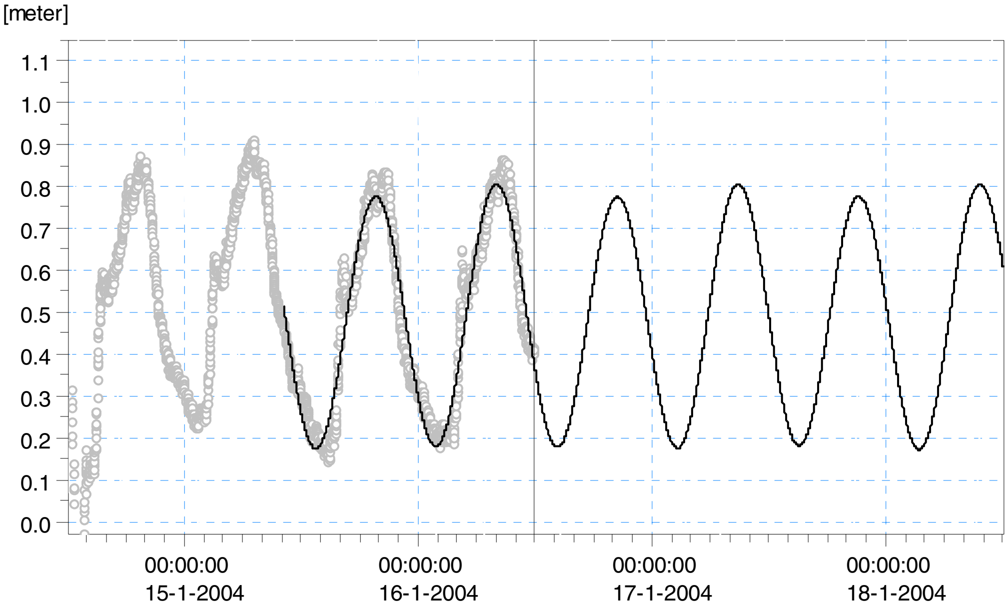

Figure 7 – Observed (○) and Estimated (-) Water Level Innovation at Schelle-409. The time of forecast is at 16-01-2004 12:00:00

5. CONCLUSIONS

A generic forecast modelling shell has been developed, which integrates robust data management facilities and forecast modelling technologies in a GIS based environment. The system facilitates easy access to a range of real-time data sources as well as the execution of modelling tools from different model suppliers. Complementing the forecast modelling shell, a new flood forecasting tool has been developed with the objective to provide fast, accurate and robust river forecasts in real-time. The forecasting technology, which has been integrated into a general data assimilation framework in the hydraulic model, applies an error forecasting technique to update the model state from one time step to the next. The new tool can be applied without restriction in tidal and backwater affected areas and does not require additional model iterations The system has been installed in a real-time data environment in northern Belgium.

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