SIMULATION OF UNCERTAINTY IN RAINFALL-RUNOFF MODELS AND THEIR STATISTICAL EVALUATION IN THE FLOREON+ SYSTEM

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ABSTRACT
Floods are the most frequent natural disasters affecting the Moravian-Silesian region. Therefore a system that could predict flood extents and help in the operative disaster management was requested. The FLOREON+ system was created to fulfil these requests. This article describes statistical evaluation of the rainfall-runoff models in the FLOREON+ system and modelling of uncertainty in the environment parameters of the model. The Monte-Carlo simulation method is used for estimating possible river discharge volumes based on the uncertainty of precipitation and meteorology forecast and provides several confidence intervals that can support the decisions in the operational disaster management. Experiments with other environment parameters and their influence on final river discharge volumes are also discussed.

Keywords: uncertainty modelling, Monte-Carlo simulation, rainfall-runoff modelling, river discharge volume statistical evaluation

1. INTRODUCTION

The main goal of the research project FLOREON+ (FLOod REcognition On the Net) is a development of prototypal open modular system of environmental risks modelling and simulation is based on modern internet technologies and platform independency. The final product of the project is going to be the system offering online communicational man-machine interface. The project results should help to simplify the process of crisis management and increase its operability and effectiveness. The main scopes of modelling and simulation are flood risk, transportation risk and water and air pollution risks. Another efficient utilization of the computing power could be computing the scenarios for the decision support. The prediction of land cover and land use changes (LULC) based on the thematic data collection (aerial photographs, satellite imagery) and application of the prediction tools bring attractive advantages to land use planning. Modelling the catchment response to severe flood events brings a possibility to improve the proposal of channel system set up and dimensioning in the scope of hydrology and water management.

2. RUNNING HYDROLOGICAL SIMULATIONS ON HPC IN THE FLOREON+ SYSTEM

HPC as a parallel environment is able to run many hydrological simulations at the same time. This allows the users to use the environment effectively and shortens waiting times for simulation results even during the high level of demand (e.g. during critical situations). Parallel computing is also very useful for model calibration in which many simulations with different calibration parameters can be run simultaneously and their results can be compared gradually.

However this comes with an implementation cost because used simulation models are not ready for such simultaneous launching. We had to solve this problem by creating multiple simulation environments integrated with preparation and finalization code. We named these functional environments Simulators and created one instance for each node and computation core that would be used to perform simulations.

Therefore when a user needs to run a simulation, he uses FLOREON+ system's Simulation Application to create new simulation and fill it with desired attributes based on the model he wants to use. The Simulation Application then calls the Run Model Web Service deployed on the HPC server and sends all given parameters. This web service utilizes the HPC environment to find a suitable Simulator instance in the pool of available instances (see Figure 1). The chosen Simulator prepares the required model and asks FLOREON+ Core Web Services for rainfall data, snow thickness, temperature and other data saved in the central FLOREON+ Database. These are used as input data to the model and the Simulator starts the simulation. Results of the simulation are sent to the

FLOREON+ Core Web Services to be saved in the FLOREON+ Database for future use. At the same time the resulting hydrographs are displayed to the user in the Simulation Application and the Simulator instance is returned to the pool of available instances.

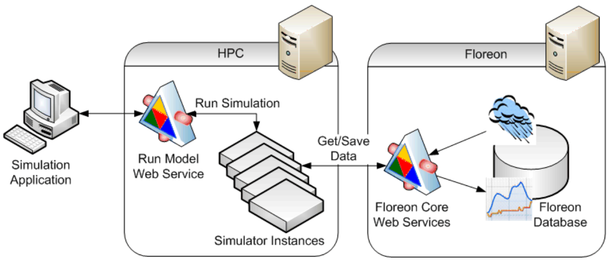

Figure 1: Running Hydrological Simulations on HPC in the FLOREON+ System

3. MODEL VERIFICATION IN THE FLOREON+ SYSTEM

It is necessary to run a lot of variants of the rainfall-runoff model to verify this model and their result are then used to run several variants of hydrodynamic simulations. The rainfall-runoff simulations take about 4 minutes to run on a one processor computer and hydrodynamic simulations take more than 1 hour. The whole simulation cascade can therefore take several days to complete, but this is not feasible in the FLOREON+ system that is intended for decision making support within operational disaster management. Since there is quite a big number of computation operations needed in order to compute the whole cascade of models considering the rainfall inputs, HPC capabilities offer a significant increase of computation speed, which is very important in operational practice, especially during the critical events.

Quality verification of the rainfall-runoff models is usually based on the comparison of the discharge volume forecast model and the actual discharge volume rates measured in these profiles. According to Refsgaard (1997), quality verification is the process of demonstrating that a given site-specific model is capable of making "sufficiently accurate" simulations. Model quality verification therefore involves running a model using measured input parameters or parameters determined during the calibration process and comparing it with real measured values. To verify the model both statistical and graphical techniques are used.

Graphical techniques provide a visual comparison of simulated and measured constituent data and a first overview of model performance (ASCE, 1993). Basic option for visual quality assessment of hydrological models is the hydrograph.

FLOREON+ web application offers visualization of hydrographs to users and then allows visual comparison of the real discharge volume with simulated hydrographs (see Figure 2). Additionally precipitations in analysed time period and flood levels are presented on the hydrograph. Displayed hydrographs then allow visual comparison of the real discharge volume with models that were created in the selected time. A plot of identity, which represents another possibility of visual quality assessment model, is also presented with the hydrograph. Plot of identity is a scatterplot of the simulated and measured data along with the identity line $y = x$. If the simulated and measured data are in basic agreement then the points in the scatterplot will line up closely to the identity line. Points lying below the line of identity indicate that the model underestimates the reality. Similarly, points lying above the line of identity indicate that the model overstates the reality (see Figure 3).

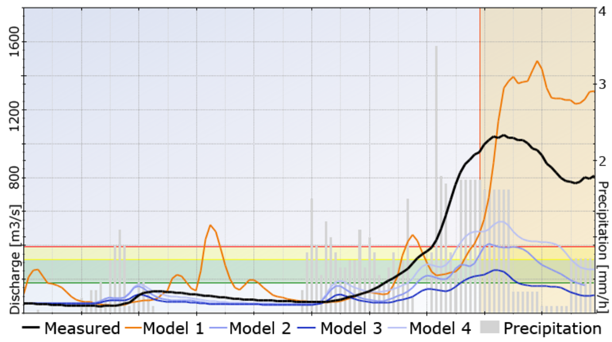

Figure 2: Hydrograph Example

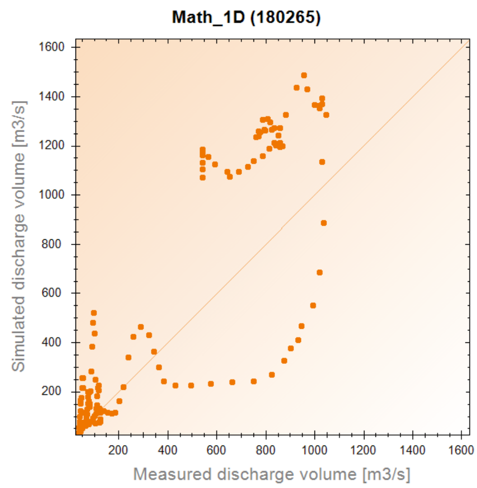

Figure 3: Plot of Identity Example

Table 1: Error Indices Example

ME [m3/s]	RMSE [m3/s]	MAE [m3/s]	MPE [%]	MAPE [%]	W [%]	MF [%]
111.8	274.0	185.6	47.8	65.0	33.6	41.4

Other methods used for model verification are the statistical methods that are based on the analysis of statistical indicators. Several error indicators are commonly used for quality model verification (see Table 1). The mean estimate error ME determines whether the model overestimates or underestimates. It is defined as

$$ME = \frac{1}{n}\sum_{i=1}^{n}\left(Q_i^{sim} - Q_i^{obs}\right), \qquad (1)$$

where Q_i^{sim} is the *i*-th simulated value for the evaluated constituent, Q_i^{obs} is the *i*-th measured observation for the evaluated constituent, and *n* is the total number of observations. To assess the total error the following indicators can also be used:

- root mean square error

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(Q_i^{sim} - Q_i^{obs}\right)^2}; \tag{2}$$

- mean absolute error

$$MAE = \frac{1}{n}\sum_{i=1}^{n}\left|Q_i^{sim} - Q_i^{obs}\right|; \tag{3}$$

- mean percentage error

$$MPE = \frac{1}{n}\sum_{i=1}^{n}\left(\frac{Q_i^{sim} - Q_i^{obs}}{Q_i^{obs}}\right); \tag{4}$$

- mean absolute percentage error

$$MPE = \frac{1}{n}\sum_{i=1}^{n}\frac{\left|Q_i^{sim} - Q_i^{obs}\right|}{Q_i^{obs}}; \tag{5}$$

- relative error in volume

$$VE = \frac{\sum_{i=1}^{n}\left(Q_i^{sim} - Q_i^{obs}\right)}{\sum_{i=1}^{n} Q_i^{obs}}; \tag{6}$$

- relative error for peak

$$MF = \frac{\max Q_i^{sim} - \max Q_i^{obs}}{\max Q_i^{obs}}. \tag{7}$$

These indicators are valuable because they indicate error in the units (*ME, MAE, RMSE*) or as a percentage (*MPE, MAPE, VE, MF*) of the constituent of interest, which aids in analysis of the results. Zero values of these indicators mean perfect fit. Singh et al. (2004) recommend to evaluate the most commonly used indicators, RMSE and MAE, as small enough, if they do not exceed half the standard deviation of the observations. It should be noted that the relative error in volume (VE) is defined in a similar manner as the percent bias (Gupta et al., 1999), steamflow percent volume error (Singh et al., 2004) and prediction error (Fernandez et al., 2005).

The current version of the FLOREON+ system represents the model output without uncertainty, see Figure 2. However, in order to represent the uncertainty of selected parameters in model scenarios, development of a software adapter for the FLOREON+ system has been started. The first results of Monte-Carlo simulations are evaluated by statistical methods and presented in the following subsections. This adapter will be able to take into account the uncertainty of selected model parameters within various prediction scenarios.

The Monte-Carlo method will also be used for the model calibration reduction, because only significant parameters will be identified by the simulation process.

4. UNCERTAINTY MODELLING USING THE MONTE CARLO SIMULATION METHOD

The Monte Carlo simulation method enables modelling of the probabilistic character of input uncertain parameters. A probabilistic distribution is used for modelling the stochastic character of the model inputs (Chudoba, et al., 2010).

By repeated realizations of the model over a random sample of input random parameters, statistic characteristics of the random output can be estimated (Atwood C. L., 1994). From the series of Monte Carlo simulation steps, it is also possible to establish an estimation of the hypothetic distribution function (Chudoba, et al., 2010).

4.1. Stochastic simulation of precipitation: a simulation approach

The stochastic modelling of the precipitation uncertainty is based on a perturbation of a precipitation matrix by the Monte Carlo simulation. The precipitation matrix *A*, which represents the precipitation forecast, has been randomly perturbed in the *k*-th Monte Carlo simulation by a constant random factor ξ_k. The aim of this uncertainty modelling is to simulate up to a 10% change of the precipitation according to the formula:

$$Apert(i,j) = A(i,j) + A(i,j)\xi_k \tag{8}$$

where the perturbation parameter ξ_k has been modelled by the uniform probabilistic distribution between [-0.1; 0.1]. These values represent the simulated 10 % uncertainty of the assumed precipitation forecast. The precipitation matrix *A* has thus been changed from the user-defined time-index, which represents time where these uncertainties are considered in the FLOREON+ model.

4.2. Scenario 1: Deterministic Cn curve parameter with a small value

In this scenario, the Cn curve parameter has been elected in by a small deterministic value (Cn = 55).
Based on the simulation procedure described in Section 4.1, a set of *k*=100 Monte Carlo simulation steps has been generated. The results of the Monte Carlo simulation model are presented in Figure 4, in which the horizontal axis represents time and the vertical axis represents the discharge volume of the simulated river at the selected station in m^3 / s. For the sake of clarity, Figure 4 also presents a 10% and 90% percentiles of the simulated discharge volumes.

In Figure 4 a small variability of the observed flow model can be seen that indicates a low sensitivity of the model to the random change of the precipitation matrix when the Cn curve parameter has a small deterministic value.

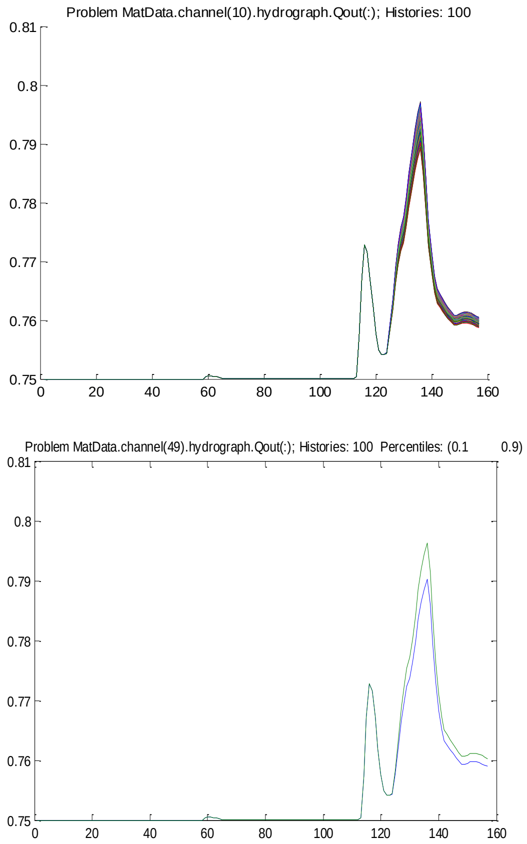

Figure 4: Discharge Volume Predictions under Scenario 1 (up); 10% and 90% Percentiles (down).

4.3. Scenario 2: Deterministic Cn curve parameter with a large value

Scenario 2 represents a similar variant to Scenario 1, except that the Cn curve parameter has a large value: Cn=95. The predicted discharge volume in the river again shows a little variability of the model, which indicates a low sensitivity of the model to the random change of precipitation. In contrary to Scenario 1, the predicted discharge volume is almost an order of magnitude larger (see Figure 4). Similarly to Scenario 1, in Figure 5 a small variability of the observed flow model can be seen that indicates a low sensitivity of the model to the random change of the precipitation matrix when the Cn curve parameter has a large deterministic value.

4.4. Scenario 3: Stochastic Cn curve parameter

Scenario 3 represents a case, when the precipitation matrix is also perturbed according to the stochastic model, as described in Section 4.1. In contrary to previous scenarios, the Cn curve parameter has been assumed to be random in the interval [CnLow, CnUpp], where CnLow = 55 and CnUpp = 95. The randomness of the Cn curve parameter has also been modelled by the uniform probabilistic distribution.

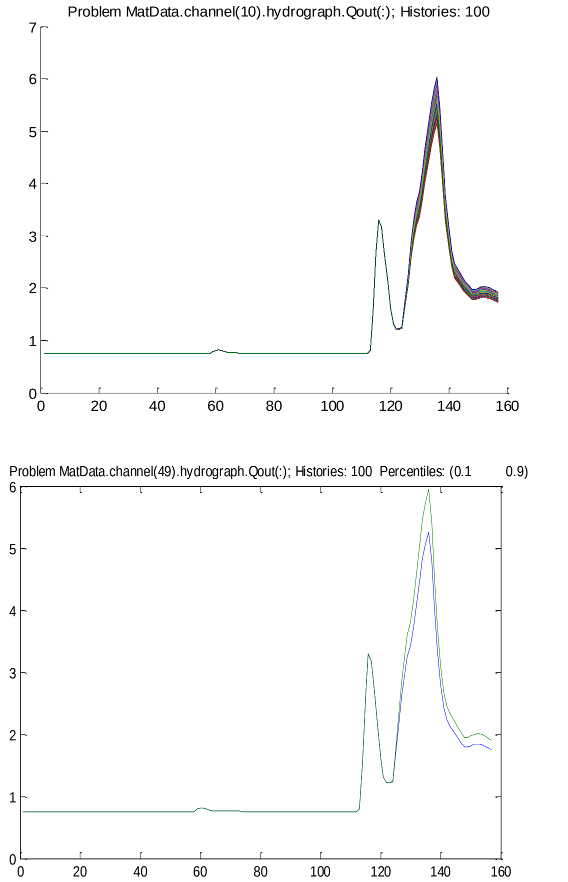

Figure 5: Discharge Volume Predictions under Scenario 2 (up); 10% and 90% Percentiles (down).

The Monte Carlo simulation model assumes that there is no dependency between the both perturbed parameters. Figure 6 shows results of the Monte Carlo simulation steps. There is a large uncertainty of the discharge volume predictions corresponding to time 120 – 140, see the y-axis, where the discharge volume oscillates between values 1-6 m^3/ s, approximately. Thus, it is obvious that the randomness of input parameters of the prediction model cannot be simply replaced by the deterministic values in this scenario. Here presented Monte Carlo simulation analyses therefore appear to be meaningful for understanding of major uncertainties in the prediction model.

5. INTEGRATION TO THE FLOREON+ SYSTEM

The experiments in the previous section proved that the uncertainty of the input parameters has a great impact on the precision of predicted simulations. Therefore it is feasible to integrate these models to the FLOREON+ system to enhance the information provided to the decision-making process. The HPC environment described in section 2 is ideal for running the Monte Carlo method for simulating the uncertainty of input parameters because it consists of many similar and independent simulations that can be executed concurrently.

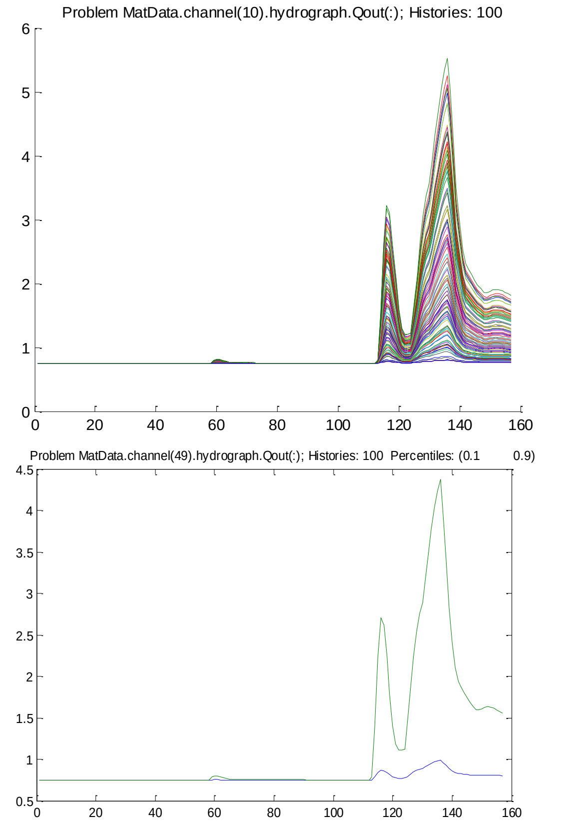

Figure 6: Discharge Volume Predictions under Scenario 2 (up); 10% and 90% Percentiles (down).

First the uncertainty values of chosen parameters had to be defined to launch these simulations automatically on the HPC cluster. Both the Cn and precipitation parameters were considered important and their possible variances set to specific probability distributions. The Cn curve parameter follows the normal distribution with small variance because this parameter is already pre-calibrated. The mean value of the normal distribution is set to the pre-calibrated value and the standard deviation is set to:

$$3\sigma = 0.05\ Cn \tag{9}$$

Precipitation uncertainty follows the uniform distribution where ξ_k is defined by the interval [-0.1; 0.1] but only precipitation forecast values are perturbed in this way. Only the prediction part of the simulations is therefore affected by the precipitation uncertainty.

After all the Monte Carlo simulations are finished on the HPC cluster, their results are collected and only their significant values are stored in the database. These significant values were defined as 5%, 15%, 25%, 75%, 85% and 95% percentiles of the simulated discharge volume for each time step to create three confidence intervals – 90% (between 5% and 95% percentiles), 70% (between 15% and 85% percentiles) and 50% (between 25% and 75% percentiles). These confidence intervals are then provided by the FLOREON+ system using the hydrographs that are shown in Figure 7.

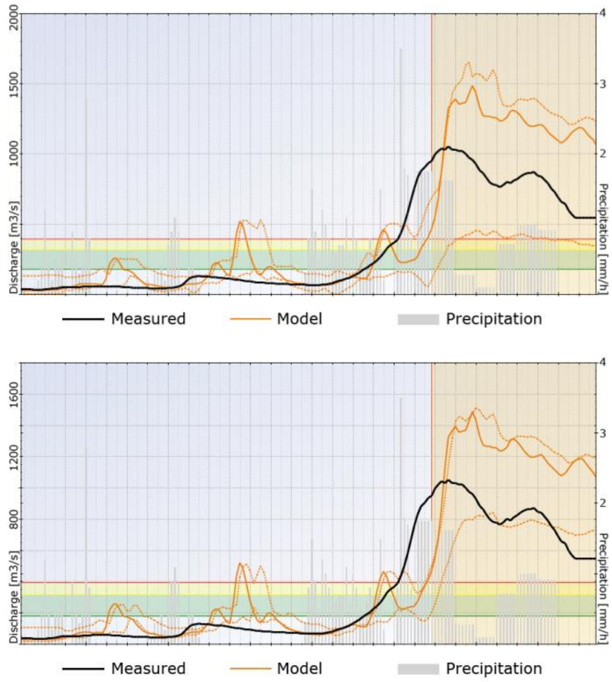

Figure 7: Discharge Volume Predictions with 90% (up) and 70% (down) Confidence Intervals.

According to Baillie & Bollerslev (1992), McNees & Fine (1996) and Christoffersen (1998), the standard evaluation of prediction interval proceeds by simply comparing the nominal coverage probability to the empirical (conditional) coverage probability (see Figure 7). The empirical coverage probability was calculated as the ratio between the number of observations that fall in the calculated prediction intervals and the total number of observations in analysed time period. Then, if the ratio overcomes the percentage of confidence interval, the interval is evaluated as successful. Numerical evaluation of selected episode with three confidence intervals can be found in Table 2.

Table 2: Evaluation of confidence intervals

Confidence interval	Values inside	Values outside	Interval Success	Is Successful
90%	45	3	93.75%	YES
70%	26	22	54.17%	NO
50%	4	44	8.33%	NO

6. CONCLUSION

This paper described the way to verify the quality of the model and the influence of the uncertainty in the input parameters to the discharge volume prediction models. The hydrographs were used for the visual quality assessment of hydrological models. A plot of identity and several error indices assessing the degree of consensus model with reality were also specified and Monte Carlo method was used to model the uncertainty of selected input parameters (precipitation and Cn curve parameters). These models were then integrated to the

FLOREON+ system and an example of their statistical and visual verification was presented.

The FLOREON+ system focuses on obtaining and analysing relevant data in real time. Prediction algorithms are then applied on the data to supply the information to the support decision-making processes in crisis management. These decisions can be supported by the predicted discharge volume on measuring stations or prediction and visualization of the flood lakes on the landscape.

Information about the quality of model predictions and uncertainties are provided in understandable form to anyone who needs to find out about the actual flood situation, whether it is an ordinary citizen, the mayor of the municipality responsible for crisis management, or expert in the field. This information can help them to understand and evaluate the situation and react to the situation appropriately.

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