# TELECOMMUNICATION MICROWAVE LINKS AS A SOURCE OF RAINFALL INFORMATION FOR URBAN RAINFALL-RUNOFF MODELLING

by

M. Fencl(1), J. Rieckermann(2), D. Stránský(1), H. Fidranská(1) and V. Bareš(1)

(1) *Czech Technical University in Prague, Department of Sanitary and Ecological Engineering, Thákurova 7, Praha, (martin.fencl@fsv.cvut.cz, stransky@fsv.cvut.cz, bares@fsv.cvut.cz, h.fidranska@seznam.cz)*

(2) *Dept. of Urban Water Management, Eawag: Swiss Federal Institute of Aquatic Science and Technology, Dübendorf, Switzerland (joerg.rieckermann@eawag.ch)*

**ABSTRACT**

In this paper we investigate potential of commercial microwave links (MWL) to capture the spatio-temporal rainfall dynamics and thus improve rainfall-runoff modelling in urban areas. Specifically, we perform numerical experiments with virtual rainfall fields and compare the results of MWL rainfall reconstructions to those of rain gauge (RG) observations. For a case study of a small sewer system, we are able to show that MWL networks in urban areas are sufficiently dense to provide good information on spatio-temporal rainfall variability and can thus considerably improve pipe flow prediction. This is especially beneficial for high-intensity rainfalls, which usually have a high spatial variability that cannot be accurately captured by RG point measurements.

*Keywords:* input uncertainty, rainfall estimation, rainfall spatial dynamics, telecommunication microwave links, urban drainage modelling

## 1 INTRODUCTION

Rainfall information with a high spatio-temporal resolution is crucial to accurately predict stormwater runoff in urban drainage systems. Conventional rain gauges (RG) can provide sufficient temporal resolution, however, as a point measurement, they cannot capture the rainfall spatial variability adequately (Berne et al. 2004). In addition, maintenance of a dense RG network is financially very demanding and local weather radars (LAWR) are not often available. In addition LAWR estimations are affected by many uncertainties such as radar shades (Thorndahl et al., 2011). Commercial microwave links (MWL) are novel source of rainfall information which could bridge this gap (Messer et al., 2006). They operate at frequencies where the raindrops are dominant source of attenuation and the MWL network is dense, especially in urban areas. However, although it seems a conceptually very interesting tool to improve urban hydrological applications, practical experience with MWL is currently lacking.

In this manuscript, we therefore investigate how data from commercial telecommunication networks can improve urban drainage modeling. Specifically, we analyze in how far the better information about spatio-temporal rainfall variability improves pipe flow predictions. As the infrastructure to acquire MWL data from telecommunication operators is just currently being implemented, we here present the results based on realistic numerical experiments. Our analysis for a suburb of Prague, Czech Republic, shows that MWL networks in urban areas are sufficiently dense to provide good information on spatio-temporal rainfall variability.

## 2 METHODS AND MATERIAL

To assess the potential of MWL in urban drainage modelling, we compare runoff predictions from MWL to those using RG observations. The analysis is based on virtual drop size distribution (DSD) fields (Schleiss, 2012) which not only enables us to estimate rainfall intensities at any location, but also to calculate the expected rain-induced attenuation of a particular MWL. Thus we can simulate the reference rainfall intensities fallen over the catchment, point rainfall intensities as seen by RG and path averaged intensities as seen by MWL. To avoid overconfidence, we perturb the virtual data with realistic observation errors for both MWL and RG measurements. These are then propagated through a hydrodynamic rainfall-runoff model with Monte Carlo simulations for all three rainfall datasets.

## 2.1 Reconstruction of space-time rainfall

**Reference rainfall fields:** The reference areal rainfall intensities are simulated using a virtual drop size distribution (DSD) generator (Schleiss et al., 2012). The simulator estimates the medium and large scale rainfall variability (1-50 km) and advection direction and velocity using radar data. The small scale variability (0.1-1 km) of the DSD is parameterized based on disdrometer data.

**Rain gauge observations:** Virtual RG measurements are extracted from the reference rainfall at one particular cell of a rainfall field. RG measurement uncertainties are modelled according to Stransky et al. (2007).

**MWL rainfall reconstruction:** The attenuation of MWL signal caused by raindrops can be calculated using T-Matrix method (Mishchenko et.al., 1998). Knowing the DSD along each particular link (by extracting it from DSD field) we can calculate its total attenuation at any time step. A simple power law relation (1) is then used to transform the specific attenuation ($k$, [dB/km]) into path averaged rainfall:

$$R = \alpha * k^{\beta} \qquad (1).$$

Empirical parameters $\alpha$ and $\beta$ are estimated for each link separately by fitting the power law estimated intensity of all events to the path-averaged one retrieved directly from the DSD fields.

The additional uncertainty caused by quantization noise and baseline is considered as normally distributed. It has been parameterized on a comprehensive dataset from a real-world case study in the greater Zurich area (Rieckermann *et al.*, 2009; Fencl, 2011).

As a typical network contains MWLs of different lengths and orientations, the two dimensional rainfall spatial variability can be reconstructed to some extent from the joint analysis of nearby MWL. For simplicity, we used the algorithm by Goldshtein et al. (2009). The algorithm first iteratively estimates the rainfall distribution along each MWL, using rainfall information from neighbouring MWL *(Figure 1).* Second, it extrapolates the estimated rainfall intensities to a regular two-dimensional grid.

## 2.2 Performance assessment

To compare the different monitoring techniques, we compute relevant performance statistics of rainfall reconstruction and pipe flow and compare them to those of the reference rainfall. For each rain event and realization (i.e., input data set for rainfall-runoff model), we compute a) the peak areal intensity ($R_{max}$), and b) the rainfall volume ($RV$), considering only the rainfall cells restricted by the catchment area. From the corresponding runoff hydrograph we compute c) the outflow volume ($QV$) and d) the peak flow at the catchment outlet ($Q_{\max}$). For comparison, we use the relative error with regard to the reference value. Its mean represents the bias and its standard deviation the uncertainty due to both limited spatial information and limited accuracy of each measuring technique.

## 2.3 Cases study – Urban Catchment in Prague, Czech Republic

The case study area is located in a suburb of Prague. The investigated catchment has an area of 2.33 km$^2$, with an impervious area of about 64 %, which is drained by a separate sewer system. The Prague urban area is covered by a dense network of many hundred MWLs. For the rainfall spatial reconstruction we selected 15 MWLs (MINI-LINK, Ericsson, owned by T-Mobile) which are located in the direct vicinity of the catchment and operate at frequency 38 GHz. For the RG information, we used one RG as is common practice in Czech Republic.

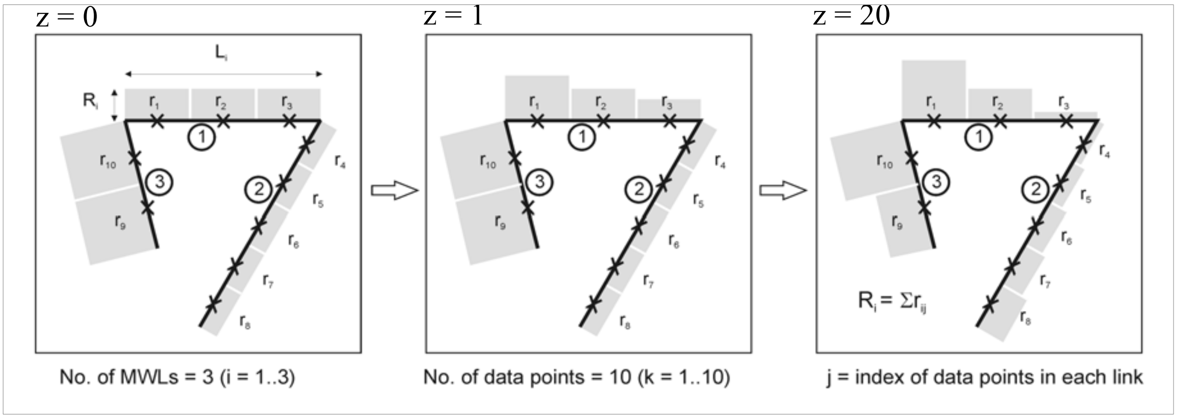



*Figure 1* – Illustration of rainfall reconstruction from the observations of three neighboring MWL. Left: Initial equal distribution of rainfall among virtual data points for a given MWL topology. Middle: Distribution estimated for a first link in the first iteration (z). Right: The reconstructed rainfall distribution along the links after the last iteration (z).

The reference rainfall fields are sampled every 1 minute and have a spatial resolution of 0.1 x 0.1 km$^2$. The original size of a rainfall field is 20 x 20 km$^2$. As the response of the catchment fundamentally depends on the rainfall characteristics, we generated three rain events: The first is a heavy convective rainfall event with low intermittency and duration of 30 min. The second has moderate convective rainfall of high intermittency and lasts 60 min. The last event has strong stratiform rainfall of low intermittency during 120 min.

To eliminate the influence of positioning the rainfall field over the study area, the relative position of the catchment to the rainfall fields was repeatedly changed to cover 25 different locations uniformly distributed over the field. This finally resulted in a comprehensive set of 75 reference areal rainfalls of a size of 7 x 7 km$^2$. From these, we computed RG data and MWL reconstructions.

The uncertainty of RG measurements follows the suggestions of Stransky et al., (2007), who investigated the uncertainty of tipping bucket rain gauges. A random sample of calibration uncertainty and losses caused by wind, wetting and evaporation is generated to approximate the probability density function of the simulated outputs with Monte Carlo simulations. The uncertainty due to quantization noise and baseline separation is sampled for each MWL independently from a normal density function (mean=0, sd=1/6 dB). As received signal levels of operational MWL have resolution quantization of 1 dB, we round the final attenuation to integer values. An additional uncertainty of MWL measurement arises from power law approximation in Eq. 1.

We use a standard calibrated hydrodynamic model for the rainfall-runoff simulations. It has been implemented in the commercial solver MIKE URBAN with the MOUSE computational engine. The model is owned by the municipality of Prague and was constructed for the general drainage masterplan for Prague. As the differential-equation model is computationally very slow, the number of Monte Carlo simulations was restricted to n=25 repetitions for each data set.

To guarantee a realistic evaluation, only those events were considered in the performance assessment, that are relevant from an engineering viewpoint, ($Q_{max,ref}$ > 10 l/s) and those that produce considerable peak runoff ($Q_{max,est}$ > 5 l/s). This was necessary, because the runoff is very sensitive to small changes in model parameters (e.g., pipe roughness coefficients) and discharge predictions at such low flows are not robust.

# 3 RESULTS AND DISCUSSION

In general, we found that the ability to predict runoff dynamics of a storm event at catchment of size of few km$^2$ depends especially on the estimation of areal rainfall intensity, its temporal dynamics and secondary on its spatial stratification.

Regarding the spatio-temporal characteristics of the rainfall fields, we found that the MWL reconstruction in general very well captures rainfall intensities averaged over whole area of catchment (*Table I*) and correctly

*Table I* – Results of the performance assessment. Colum 1 and 2 compare the statistics of the measurements to those of the reference rainfall. Column 3 and 4 compare the resulting peak flows and flow volumes. The standard deviation is given in brackets.

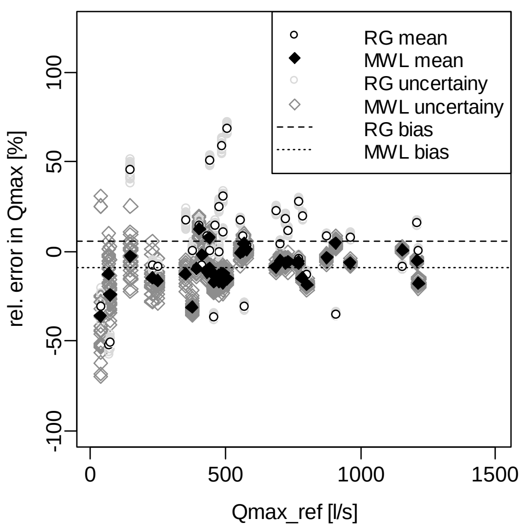
| | **RV – mean rel. error** | **Rmax – mean rel. error** | **QV – mean rel. error** | **Qmax – mean rel. error** |
|---|---|---|---|---|
| **RG** | 4 % (14 %) | 34 % (27 %) | 6 % (26 %) | 6 (26 %) |
| **MWL** | -3 % (10 %) | 0 % (10 %) | -12 % (11 %) | -9 (11 %) |

reproduces the location of peak rainfall intensities. However, it averages the local maximums and minima. As we consider only uncertainties due quantization noise, baseline separation and A-R power law relationship (1), the uncertainties of MWL rainfall estimates are almost independent of rainfall intensities, because the parameter β of a power law (1) almost equals 1 at 38 GHz frequencies (Berne, 2007).

In contrast to MWL, a RG can capture rainfall intensity maximums and minimums in its direct vicinity, however, the areal intensity estimates are less reliable (*Table I*). This applies especially to high intensities, because the rainfall spatial variability is in general higher during periods of strong rainfall and RG, as a point measurement, cannot reflect the spatial distribution of rainfall. In addition, the accuracy of point estimates from tipping bucket RG decreases with growing intensity. Therefore, the areal intensities of light rainfalls are, on average, better reproduced by RGs in contrast to the MWL network, which, in contrast, better reproduces heavy rainfalls.

Regarding the performance to predict sewer discharges, the threshold for evaluating the rainfall induced flows ($Q_{max\ ref}$> 10 l/s and $Q_{max\ est}$> 5 l/s) was exceeded by 40 of the 75 rain events. For these, we found that the MWL-based flow predictions match the runoff from reference rainfall better during high intensity rainfall periods and those from RG data during low intensity periods (*Figure 2*). Although MWL-based flow predictions have a larger bias, this occurs mostly during periods of low or moderate flows, where absolute deviations are not critical. In contrast, the standard deviation of the results is considerably lower than that from RG (*Table I*). The visual comparison of hydrographs revealed that MWL-based predictions in most of the cases capture pipe flow temporal dynamics better than RG estimates (not shown).

Unfortunately, although we took great efforts to assess measurement uncertainties, our results do not yet include the effect of antenna wetting for the MWL observations. On the one hand, this might increase both systematic and random observation errors, especially during high intensity rainfalls. On the other hand, MWL networks are often extremely dense in urban areas, which should allow us to improve the accuracy of MWL observations by considering many links, which should contain redundant information.



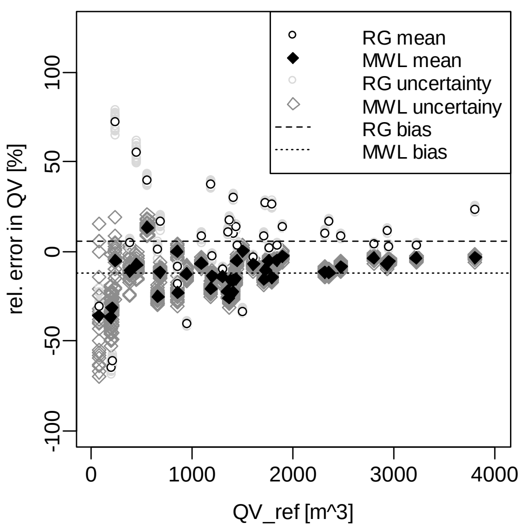




*Figure 2* – Relative error for different peak flows (left) and outflow volumes (right).

# 4 CONCLUSIONS

In our study, we found that better information from Telecommunication Microwave Links about spatio-temporal rainfall variability has a potential to improve pipe flow predictions compared to those based only on traditional RG observations. Our results show, that, first, MWL rainfall reconstruction very well reproduces areal averaged rainfall intensities but the path-average information smoothes the local maxima and minima. Interestingly, although MWL contain these fundament biases, we found, second, that they reproduce the runoff dynamics better than point RG measurements, which simply lack the spatial rainfall information. The reliability of point measurement is especially low for high intensity convective rainfalls with their higher spatial variability. Third, we find that runoff from MWL observations better reproduces initial runoff. This is, because they can capture rainfall intensities over the whole area of catchment and thus better observe the onset of precipitation. This could greatly improve the real time control of drainage systems. In the future, the MWL could complement RG point measurements with the missing spatial rainfall information. Thus, they can reduce input uncertainties in rainfall-runoff modeling and improve discharge predictions.

# 5 ACKNOWLEDGEMENTS

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