RAINFALL RETRIEVAL FROM TELECOMMUNICATION MICROWAVE LINKS – INFLUENCE OF REFERENCE RAINFALL OBSERVATIONS

by

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ABSTRACT

In this paper, we investigate how rainfall observations from telecommunication microwave links improve when the link is adjusted against different reference rainfall data from rain gauges or distrometers. Based on field data and numerical experiments we assess the performance of four different rainfall retrieval models, which require different levels of precipitation information.

Keywords: telecommunication microwave links, reference rainfall data, drop size distributions, data quality

1 INTRODUCTION

Commercial microwave links from telecommunication networks (MWL) are a new source of rainfall information which has a potential to improve incomplete observations from rain gauges and improve the accuracy of weather radars (Atlas and Ulbrich, 1977; Messer et al., 2006). Especially for urban rainfall monitoring, MWLs are conceptually interesting, because, among other things, MWL networks are already built and could provide rainfall information at virtual no additional cost (Rieckermann et al., 2009).

While this area has seen considerable progress in recent years, it is not clear, in how far the data are relevant for urban hydrological applications. End users, such as sewer operators, would like to know the accuracy of such measurements. One question is, whether retrieved rainfall intensities are becoming more accurate when adjusted against ground truth rainfall data from rain gauges or distrometers. In this study, we investigate in how far available "ground truth" precipitation data from existing monitoring stations improves the retrieval of path-average rainfall intensities. Specifically, we assess the performance of four different rainfall retrieval models of varying complexity, which have different assumptions and require different levels of precipitation information.

2 METHODS

2.1 Microwave link attenuation due to rain drop scattering

Point-to-point radio systems, which are typically realized with microwave links that operate at frequencies between 20 and 60 GHz, are mostly disturbed by i) signal absorption by snow and dust particles, ii) signal absorption and scattering by water vapor and atmospheric gasses, and iii) signal absorption and scattering caused by raindrops. In millimeter bands, rainfall is not only the major source of attenuation (Brussaard and Watson, 1994), but it also directly depends on the drop size distribution (DSD). The total rain-induced attenuation can be calculated as a sum of extinction cross-sections of all raindrops along the MWL, using the T-matrix method (Mishchenko and Travis, 1998).

2.2 Rainfall retrieval from microwave links

Since there is not a unique relationship between specific attenuation and path averaged DSD (Townsend et al., 2009), rainfall intensities (R, [mm/h]) are usually estimated from the specific rainfall-induced attenuation (k, [dB/km]) with a power law model:

$$R=\alpha k^{\beta} \quad (1)$$

with empirical parameters α and *β*. The validity of this model mainly depends on a low variability of the DSD along the link, and the proper estimation of α and *β*. An accurate determination of rainfall-induced attenuation depends on a low MWL signal quantization and the proper separation of other sources of attenuation, i.e., removal of the dry-weather baseline. In this paper, we compare four different MWL rainfall estimation models, which differ in the estimation of model parameters, bias correction and data requirements:

The ITU model is based on Recommendation ITU-R P.838-3 of International Telecommunication Union (ITU-R, 2005), which is being used for designing MWLs. The α, β parameters of the R-k power law (1) are defined as $\beta= b^{-1}$ and $\alpha= a^{-\beta}$. Depending on the link characteristics, empirical values are provided for *a* and *b* for different regions. Although no reference rainfall data are required, local rainfall characteristics or MWL properties cannot be taken into account.

The PL model estimates *α* and *β* from MWL attenuation using local rain gauge data, e.g. with ordinary least square regression. To obtain representative results, this ideally requires a large data set of rainfall and attenuation data for calibration. Ideally, an entire one year period should be used for the calibration, to adjust the model, for a whole range of possible types of precipitation.

The WAC model extends the PL model with a correction for a wet antenna attenuation (see below), which is applied before parameter estimation. The wet antenna correction is processed according to (Kharadly and Ross, 2001), which apparently improved the data quality in previous studies (Zinevich et al., 2009).

The Kharadly model uses a simple empirical exponential relationship

$$A_{wa} = C\cdot[1-\exp(-d\cdot A_m)] \quad (2)$$

where A_{wa} [dB] represents the wet antenna attenuation, *C* [dB] the maximal expected wet antenna attenuation, *d* [dB^{-1}] the estimated empirical parameter and A_m [dB] the total attenuation. For adjustment, *C* was taken from literature to 3 dB (Kharadly and Ross, 2001; Leijnse et al., 2008) and *d* was estimated from attenuation and rainfall.

Finally, **the DSD model** is based on the assumption, that DSD measured by disdrometer, sufficiently represent the DSD along the link causing the MW signal scattering. The rain-induced attenuation is a function of the path-average DSD and extinction-cross section, which mainly depends on MW frequency and polarization. The disdrometer provides both rainfall intensity and expected attenuation data. Those two data sets are used in Eq. (1) to compute *α* and *β* parameters, as for the PL model described above. The model was calibrated for two years long period of disdrometer measurements.

To assess the performance, we compared retrieved rainfall to the computed values with regard to relative errors in rain volume and the RMSE of intensities. As the parameter estimation of PL and WAC model depends highly on rainfall characteristics of rainfall calibration data set we carefully selected form the available data uniform rain events, where the point reference measurements are comparable to path-average estimates. To assess the influence of selected calibration and validation events, we performed a cross-validation analysis for PL and WAC models.

3 MATERIAL

The rainfall retrieval was tested on real world data, which included received signal levels of a MWL (38 GHz, 2876 m long, vertical pol., 0.1 dBm quantization, dt~ 3min), measurements from one distrometer (Distromet RD 80, dt=1 min, distance to MWL: 100m), three rain gauges (distance to MWL: 0m, 500m, 2km), as well as weather radar data from Meteoswiss (Δx= 1x1km2, Δt= 5min). Sixteen rainfall events relevant in terms of urban storm water management (V_{tot} > 2mm, $R_{mean,\ 15\ min}$ > 1 mm/h) were selected for model evaluation. All of the events were measured between May and September. In addition, virtual DSD fields (Δx= 0.1x0.1km^2, Δt= 1min) were generated from a stochastic DSD simulator (Schleiss et al., 2009) based on the radar and distrometer observations for a rain event with a duration of 60min to explore the impact of errors in ground truth information.

4 RESULTS AND DISCUSSION

4.1 Model calibration and performance

The parameters are constant for the ITU and DSD model (*Table I*). The parameters sets of the PL and WAC model, estimated by cross-validation, are illustrated in *Figure 1*. The relatively broad range of parameter values indicates that both models are sensitive to the selection of rain events for calibration. For the WAC model, the shift of α towards higher values is caused by wet antenna correction. The estimates correspond well with values reported in literature (Berne and Uijlenhoet, 2007).

Regarding the model performance, our results show, interestingly, that using more detailed information apparently does not improve the results. As depicted in *Figure 2, left*, the best performance is obtained for the ITU model, which has almost no bias (-3.1%) and the least variability. The estimates from the DSD model are systematically overestimated (25%) and, although the PL (6.5%) and WAC model (7.9%) are practically unbiased, their variability is rather large. This is most probably due to uncertainty in the estimated model parameters. As the PL and WAC model performance was evaluated for the whole set of the estimated parameters, the results include additional uncertainties due to model calibration. This is not included in the ITU and DSD models. The range of estimates for both PL and WAC models for particular rain events can be seen in *Figure 2, right*. The poor performance of the DSD model indicates that, even for widespread events, point DSD measurements are not sufficient to compute path-average attenuation. To some degree, this also explains the relatively poor performance of the WAC model. The inferior performance of both the PL and WAC models with regard to the ITU model can be explained by the limited amount of rain events used for their calibration. Paradoxically, the pre-selection of calibration events seems to penalise the PL and WAC models, because all sixteen events are later included in a final performance assesment.

Table I – Model parameters obtained during calibration.

	α	β	d	C	
ITU	model	2.83	1.13	-	-
PL	model	2.68–3.61	0.96–1.16	-	-
WAC	model	3.54–4.63	0.90–1.16	0.012–0.064	3
DSD	model	3.68	1.08	-	-

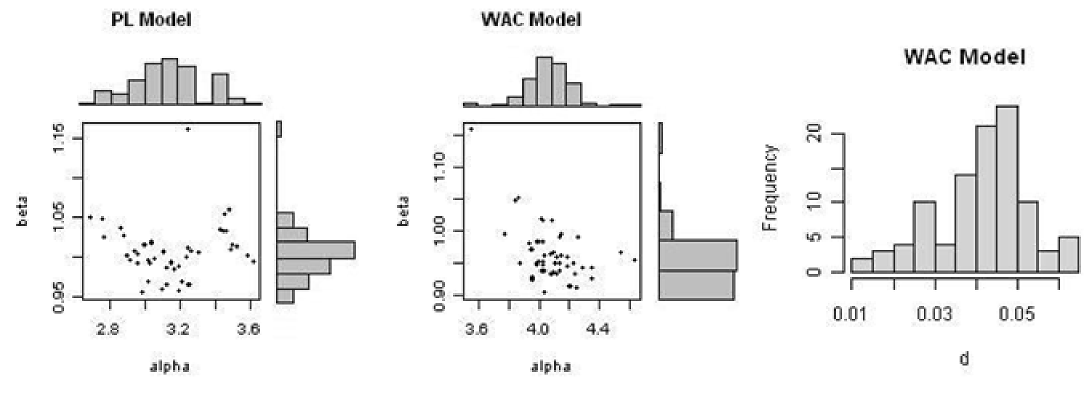

Figure 1 – Scatterplots of model parameters obtained from calibration.

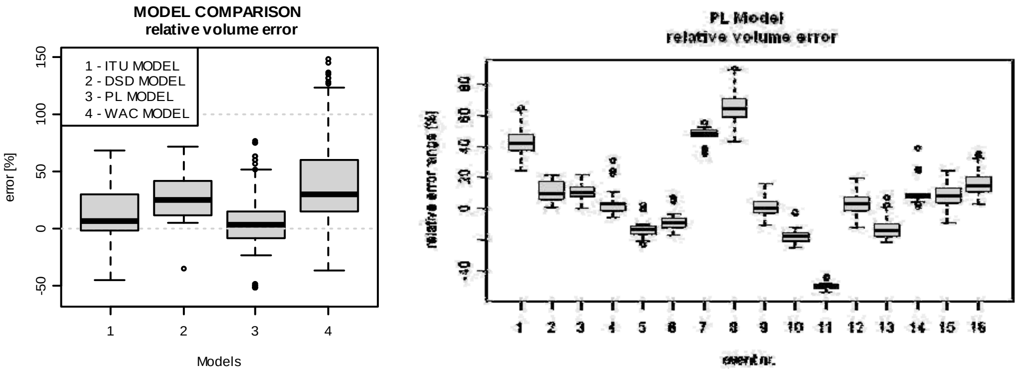

Figure 2 – Left: Comparison of the different models, *Right:* Performance of the PL model for the investigated rainfall events.

When comparing estimated to measured intensities (not shown), we find that the scatter has a heteroscedastic tendency in all models. In addition, the relative error increases with increasing rainfall intensity. This confirms our expectations, because the high intensity rainfalls are usually convective events. In addition, the analysis of rainfall data from the other RGs indicates, that the observed scatter is due to spatial rainfall variability. This is also supported by the results from the numerical experiments with the DSD fields.

4.2 Influence of the spatial variability of rainfall

Based on our simulation results, we can show that much of the observed variability can be explained by uncertainty in the reference measurements of rain gauge and distrometer. The estimated rainfall from MWLs correlates much better with the path-averaged than with point rainfall measurements.

The scatterplots in *Figure 3, left and middle,* show the path-averaged rainfall estimates from a MWL that has been adjusted to the point observations of a virtual RG. In the left plot, the estimates are compared to point observations from a gauge, which results in wide scatter (RMSE= 6.8 [mm/h]). When the same path-averaged estimates are compared to the true path-averaged rainfall (*middle*), the estimates are much better (RMSE= 1.27 [mm/h]). When the MWL is adjusted to path-averaged rainfall intensities (*right*), even the slight bias disappears (RMSE= 0.46 [mm/h]). This demonstrates, first, that the limited information from point observations can explain about 50% of the observed variability in performance (*Figure 2*). While, here, the results were obtained for a low intensity rainfall, the difference between path averaged and point measured rainfall would be even more striking for strong convective events. Second, the results of *Figure 3, middle,* suggest that even MWL rainfall estimates from links that have been adjusted to a nearby rain gauge, are in good agreement with the true path average rainfall.

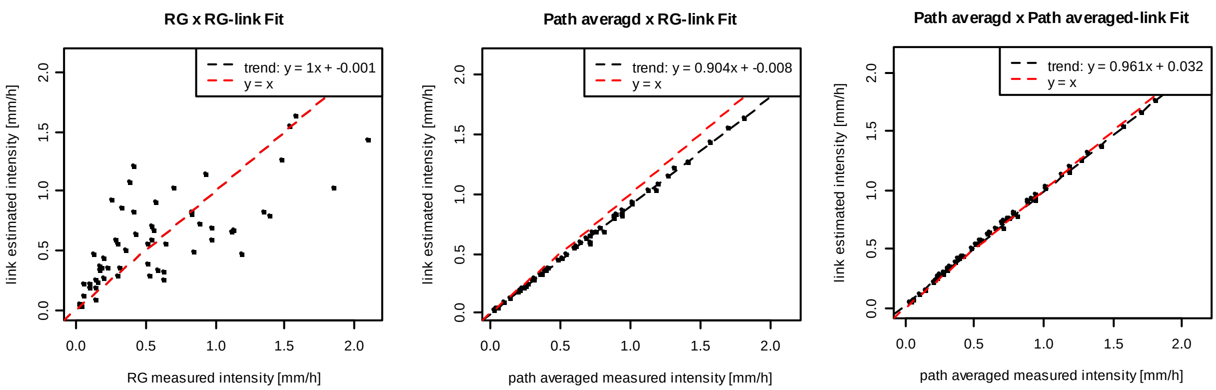

Figure 3 – Scatter introduced by DSD variability along the MWL. *Left:* Comparison of RG measurements to link estimates that were fit to RG data ((*left*) and are considered as ground truth for parameter estimation. *Middle: Right:* Resulting scatter when path-averaged rainfall intensities are used to fit the parameters and also considered as ground truth.

5 CONCLUSIONS

In this paper, we investigated in how far different type of reference rainfall observations improves rainfall retrieval from commercial microwave links. This is an especially important question for end-users, such as sewer operators, who would like to know the benefit of additional investments, such as disdrometers, when working with link observations. Surprisingly, our results suggest that the ITU model provides very good results without any adjustments. We also find that the performance of more advance retrieval models is very much dependent on the rainfall sample used for their calibration. Thus, they should only be applied when more than one year of rainfall and link attenuation data are available for calibration. The poor performance of the DSD model indicates that point DSD measurements are not suitable for calculating path-average attenuation. To some degree, this could explain the poor performance of correcting for antenna wetting. One important conclusion from our work is that the performance evaluation of path-average MWL rainfall estimates is problematic when point observations, e.g. from rain gauges, are used as a reference. Unfortunately, to evaluate the quality of link rainfall estimates field experiments are mandatory, because numerical experiments can only answer some very specific questions.

In conclusion, the path-average rainfall rates from MWL data behave very much as expected and show lower peak intensities as well as longer event durations compared to raingauge measurements. Despite some limitations, our results suggest that MWL data represent a relevant source of information about path-averaged intensities and can thus improve urban rainfall-runoff studies.

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