P7R.14 **A NEURAL NETWORK BASED METHOD TO ADJUST WEATHER RADAR ESTIMATES OF RAINFALL TO RAIN GAUGE MEASUREMENTS USING THE VERTICAL REFLECTIVITY PROFILE**

Reinhard Teschl *, Walter L. Randeu and Franz Teschl

Graz University of Technology, Dept. of Broadband Communications, Austria

1 INTRODUCTION

Today the weather radar is an indispensable tool in the field of meteorology and hydrology. Its gapless spatial coverage and high temporal resolution are among its most evident advantages when detecting precipitation. But other than rain gauges which measure the rain rate R directly on the ground, the radar measures the reflectivity Z aloft and the rain rate has to be determined over a Z-to-R relationship. Besides the fact that the rain rate has to be calculated from the reflectivity many other sources of possible errors are inherent to the radar system: underestimation of the rainfall because of shielding effects and partial beam filling, attenuation caused by water present on the radome during and shortly after rainfall at the radar site (Germann, 1999). Worth mentioning are especially errors caused by the vertical precipitation structure and profile of reflectivity (VPR).

Because of the sources of errors mentioned above, the accuracy of the radar often is not sufficient for quantitative applications, and the development of methods to enhance the measuring accuracy has been a field of research for many years. To mention in this connection are methods to adjust radar estimates of rainfall to rain gauge measurements (e.g. Köck, 1999). Also artificial neural network (ANN) techniques have been used for ground rainfall estimations. Xiao and Chandrasekar (1997) trained a backpropagation neural network (BPNN) to predict ground rainfall. Liu et al. (2001) and Xu and Chandrasekar (2005) developed radial basis function (RBF) neural networks for radar rainfall estimation.

This paper presents a method to use the VRP over rain gauge sites to train a BPNN to predict the rainfall depth measured at ground level.

* *Corresponding author address*: Reinhard Teschl, Graz University of Technology, Department of Broadband Communications, A-8010 Graz, Austria; e-mail: reinhard.teschl@tugraz.at

Extensive analysis of rain gauge and weather radar data in Austria has shown that the metering precision of the radar largely depends upon the type of rainfall. Therefore the adjustment methodology takes into account the type of rainfall present. The VRP provides this information. The results indicate that the relationship determined by the neural network model between VRP and rain rate measured on the ground, is also representative for sites with similar elevation and distance from the radar. Therefore the model can provide better estimations for ground rainfall also for areas without rain gauge.

2 DATA AVAILABLE

For the processing rain-gauge and radar data were available. The data sets extend over a 30-month period from April 2002 to October 2004. The rain gauges are working on the tipping bucket principle with a resolution of 0.1 mm. Their temporal resolution is 15 minutes. Referring to the abovementioned sources of errors of the radar system, it should be noted that naturally also rain gauges feature measuring errors. The rain gauge data used here are officially controlled and verified by the Hydrographische Landesabteilung Steiermark (Department for Hydrography of the Province of Styria).

Reflectivity measurements are gained from the Doppler weather radar station on Mt. Zirbitzkogel. The designated radar is a high-resolution C-band weather-radar situated on an altitude of 2372 m (above Mean Sea Level, MSL). The distance between rain gauge and weather radar is about 70 km. Table 1 shows the radar specifications.

Table 1: Technical specifications of the weather radar on Mt. Zirbitzkogel

Time interval between measurements	5 minutes
Resolution in measured reflectivity	14 levels of rain-rate
3-dB-Beamwidth	1°

Table 1: (continued)

Minimum elevation angle	0.8 °
Spatial resolution of the volume element	1x 1 x 1 km^3
Applied Z-to-R relationship	Z = 200 R1.6
Instrumented range	220 km

3 NEURAL NETWORK MODEL

According to Liu et al. (2001) the rainfall estimation can be viewed as a complex function approximation problem where the ground rainfall can be potentially dependent on the four-dimensional structure (three spatial dimensions and time) of precipitation aloft.

An artificial neural network is a data-driven technique that characterises the behaviour of a system by finding a relationship between an input and a target time series. In this case the VRP above a rain gauge forms the input and the rain gauge measurement the output of the network. The neural network performs the function approximation based on historic volumetric radar and rain gauge data. As ANNs are in principle capable of performing any input-output relationship, it has to be ensured that the model is able to generalize. This means that the ANN describes not only the relationship between the training input and target data sets but that the relation found can also be applied to new data sets. This can be guaranteed by dividing the data available into training, validation and test sub sets, and to stop the training when the error on the validation data set increases. For this study one half of the data sets available were used for training and one quarter each for validation and training. The selection was carried out randomly. Though it was ensured that all subsets contained data from all seasons.

An analysis was carried out to define an appropriate input vector. As the lowest visible elevation level above the rain gauge site is 3.5 km (below denoted by level 1) a time lag between radar and rain gauge measurements was expected. The analysis showed that the correlation of the radar reflectivity at level 1 with the rain gauge measurements 5-minutes shifted is highest (see Table 2) and the root mean square error is lowest (Table 3). Therefore the network was trained on the 5-minutes shifted rain gauge values. Reflectivity values from level 1 to level 4 (3.5 to 6.5 km elevation) were included into the input vector. Another input parameter was the highest level where reflectivity unlike zero was measured. This parameter was taken as an indicator concerning the type of rainfall present.

Table 2: Correlation coefficient between radar and rain gauge measurements at different elevation levels and time lags. The distance between the levels equals 1 km.

Time shift [min]	Level 1	Level 2	Level 3	Level 4
0	0.4685	0.3706	0.2998	0.2919
5	0.5011	0.4153	0.3175	0.3072
10	0.4848	0.4200	0.3092	0.2854
15	0.4570	0.4019	0.3240	0.2564
20	0.4212	0.3777	0.3202	0.2673

Table 3: Root mean square error (RMSE) of the radar data at different elevation levels and time lags with respect to the rain gauge measurements. The distance between the levels equals 1 km.

Time shift [min]	Level 1	Level 2	Level 3	Level 4
0	0.1699	0.1787	0.1835	0.1855
5	0.1683	0.1771	0.1838	0.1863
10	0.1698	0.1771	0.1841	0.1868
15	0.1718	0.1777	0.1834	0.1875
20	0.1744	0.1789	0.1832	0.1870

4 RESULTS AND DISCUSSION

Several BPNNs have been trained to determine the network architecture showing the best performance on the validation data. A configuration with 3 layers and 7 neurons in the hidden layer exhibited the best performance as measured by the RMSE. Then the model was applied to the test data. Both correlation and root mean square error could be improved compared with the pristine radar data of Level 1. Table 4 shows the figures.

Table 4: Improvement of the ANN-Model compared to pristine radar data.

	Pristine radar data	ANN-Model
Correlation	0.5675	0.5941
RMSE	0.1538	0.1285

It was also examined if the ANN-Model is also applicable to other sites. For this purpose the model was tested with radar data over an other rain gauge site and the corresponding rainfall measurements. Data series from the weather station Gleinstätten, were used. The sites exhibit similar elevation and distance from the radar. Table 5 shows that both correlation and RMSE could be improved. The figures refer to the whole investigation period (from April 2002 to October 2004).

Table 5: Application of the ANN-Model to an other site (Gleinstätten).

	Pristine radar data	ANN-Model
Correlation	0.3016	0.3748
RMSE	0.1958	0.1902

It is notable that the model that was calibrated for the site at Kitzeck shows also good results when applied to site Gleinstätten about 10 km far. This makes the model applicable to an area around the station calibrated.

5. REFERENCES

Germann, U., 1999: Radome attenuation – a serious limiting factor for quantitative radar measurements? Meteorol. Z.,8,85-90.

Köck, K., 1999: Nationale und internationale Wetterradarnetze und ihre Kalibrierung mittels Regenmesserdaten für quantitative Verwendung. Doctoral Thesis, Graz University of Technology, Austria.

Liu, H., Chandrasekar, V. and G. Xu, 2001. An adaptive neural network scheme for rainfall estimation from WSR-88D obsservations. Journal of Applied Meteorology, 40, no. 11, 2038-2050.

Xiao, R. and V. Chandrasekar, 1997: Development of a neural network based algorithm for rainfall estimation from radar observations. IEEE Transactions on Geoscience and Remote Sensing, 35, 160-171.