New Method for Detection of Precipitation Based on Artificial Neural Networks

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Abstract – **Detection of precipitation based on the received signal level of commercial microwave links has been increasingly used in the mountain areas where meteorological radars have limited ranges, and placing rain gauges is impossible due to terrain morphology. In this paper, focused time-delay neural networks were trained to detect the appearance of precipitation based on the received signal level. The detailed testing of the trained artificial neural networks was done with the data obtained on the same link, which were not used for model development. The results show that the proposed method based on neural networks can be used for accurate precipitation detection in significantly shorter time comparing to the previous methods.**

Keywords – **precipitation detection, focused time-delay neural networks, microwave link, received signal level.**

I. Introduction

Accurate detection of precipitation using meteorological radars or rain gauges is almost impossible in complex terrains with rapid changes in altitude, such as in the case of mountainous terrain, because meteorological radars have limited ranges due to absence of line of sight in the valleys between mountain peaks and placing rain gauges is impossible due to terrain morphology.

To overcome the foregoing problem, scientists have given the various theoretical descriptions and experimental proofs of the influence of precipitation on the signal attenuation, for years. Stratton gave the first theoretical description of the influence of precipitation on the signal attenuation in 1930 [1], with a focus on determining of the unwanted interference occurring under the influence of rain and fog during the propagation of very short radio waves. The first experimental proof of this effect is given by Mueller in 1946, where he studied the propagation of signals at frequencies of the 50 GHz [2]. Later, during the seventies, researchers who have studied meteorological radars, came up with the idea to measure the amount of precipitation based on the signal attenuation that occurs along a microwave link in the frequency range 10-30 GHz [3]. Since then, several experiments with a purpose built microwave links have been performed, in order to determine the amount of precipitation occurring along the line [4]-[8]. Messer in 2006 showed that it is possible to measure the amount of precipitation based on the data obtained on the existing commercial microwave links [9]. The use of microwave commercial links has two main advantages: first, they are widespread over the world [10], and second, they operate at frequencies of tens of GHz, where precipitation is the most important factor in the occurrence of the signal attenuation. Therefore, this technique can be applied in areas with a small number of rain gauges, as in the case of mountainous areas and developing countries.

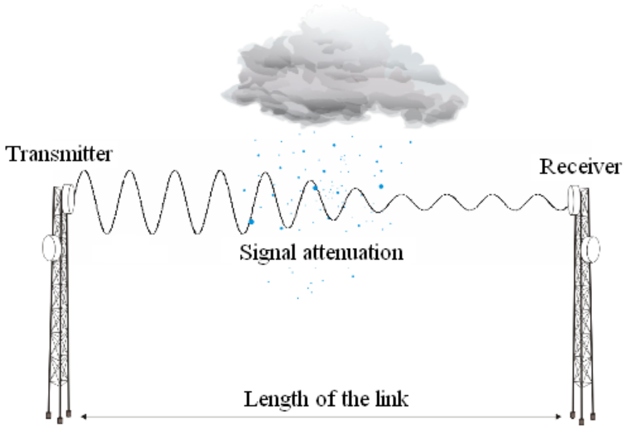

Fig. 1. Signal attenuation of the microwave link, which occurs due to the precipitation occurrence

Fig. 1 illustrates the signal attenuation of the microwave link, which occurs due to the precipitation occurrence. Signal attenuation that occurs on commercial microwave links have been studied theoretically and practically in order to detect the precipitation [11].

The problem of precipitation detection can be solved by using the numerical method that is based on the detection of precipitation using information about the received signal level (RSL) of commercial microwave link [12]. The method

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described in [12], is based on the fact that the raindrops scatter and absorb electromagnetic radiation at the microwave frequencies. However, very complex calculations require a lot of time, and the implementation of numerical method in real systems is limited.

Neural-network computational modules have gained recognition as an unconventional and useful tool for use in the microwave technique [13]-[22]. In this paper we present a new method for the detection of precipitation using RSL of commercial microwave link, based on focused time-delay neural networks (FTDNN). In this way, the whole process of detection of precipitation is made more efficient.

The paper is structured as following: after the Introduction, in Section II the procedure for detection of precipitation that occurs on microwave commercial link using numerical method [12] is described. The proposed artificial neural network (ANN) based method is described in Section III. In Section IV the numerical results of detection of precipitation are presented and discussed. The main conclusions are given in Section V.

II. Detection of Precipitation Using Numerical Method

The problem of detection of periods with precipitation, based on the recorded data of RSL, can be viewed as a problem of pattern recognition of time series [12]. For a small data sets, detection of precipitation can be done by a human observer, who has experience in comparing RSL data with rain gauge records. However, for a large data sets, this is not feasible. Therefore, the numerical method for the detection of precipitation is developed [12]. This method is based on the algorithm which is described below.

For each time step, t, a short section of the RSL data, R, with length $2L$ (a length of 256 points was found to perform best), is taken:

$$R(t) = \{R_k \mid k \in \{t-L,...,t+L\}\}\ , \tag{1}$$

from which the Fourier transform is calculated via fast Fourier transform (FFT):

$$\mathcal{F}(f,t) = \mathrm{FFT}(\omega R(t))\ , \tag{2}$$

where ω – is the Hamming window.

As only the amplitude spectrum is of interest, power spectral density is used for further analysis:

$$P(f,t) = \frac{2\,|\mathcal{F}(f,t)|^2}{F_S \sum_0^L \omega^2}\ , \tag{3}$$

where F_S – is the sampling rate and $\sum_0^L \omega^2$ – is the sum over all Hamming window weights. It should be noted, that the received spectrum is just a different representation of the short time series section around t, only in the frequency domain.

To simplify the detection of precipitation, a normalisation of the spectra has to be applied. The normalization is performed with respect to the mean power spectral density for dry period:

$$P_{\mathrm{norm}}(f,t) = \frac{P(f,t)}{P_{\mathrm{mean\ dry}}(f)}\ . \tag{4}$$

The normalized power spectral density varies depending on the frequency and the weather conditions at the link. In the case of appearance of precipitation, normalized power spectral density has a maximum value at lower frequencies, while in the absence of precipitation, the highest value of normalized power spectral density is obtained for higher frequencies.

Since normalized power spectral density depends on the frequency, the normalized frequency at which the spectrum is divided into two parts, f_{divide}, is used. This frequency is determined empirically so that the data obtained by calculation best fit the data obtained using rain gauges. Sums of the normalized amplitudes in the case of low ($f \le f_{\mathrm{divide}}$) and high ($f > f_{\mathrm{divide}}$) frequencies are calculated using the normalized power spectral density:

$$P_{\mathrm{sum\ low}}(t) = \sum_{f \le f_{\mathrm{divide}}} \frac{P_{\mathrm{norm}}(f,t)}{N_{\mathrm{low}}}\ , \tag{5}$$

$$P_{\mathrm{sum\ high}}(t) = \sum_{f > f_{\mathrm{divide}}} \frac{P_{\mathrm{norm}}(f,t)}{N_{\mathrm{high}}}\ . \tag{6}$$

Detection of periods with precipitation is performed on the basis on the value of the difference between the sums of the normalized amplitudes in the case of low and high frequencies, $P_{\mathrm{sum\,diff}}$.

$$P_{\mathrm{sum\ diff}}(t) = P_{\mathrm{sum\ low}}(t) - P_{\mathrm{sum\ high}}(t)\ . \tag{7}$$

If the difference $P_{\mathrm{sum\ diff}}$ exceeds a certain threshold σ, the period is marked as wet, otherwise, the period is marked as dry:

$$t = \begin{cases} \mathrm{wet} & \mathrm{if} \quad P_{\mathrm{sum\ diff}}(t) > \sigma \\ \mathrm{dry} & \mathrm{if} \quad P_{\mathrm{sum\ diff}}(t) \le \sigma \end{cases}\ . \tag{8}$$

III. Proposed Neural Model

The numerical method proposed in [12], requires a lot of time, and this is in practice very undesirable. In order to reduce the time needed for the precipitation detection, here a new method based on ANNs is proposed.

An ANN consists of a number of interconnected processing elements called neurons, and operates similar to natural nervous system. One of the simplest structures of the neural networks is a multi-layer perceptron (MLP) one, Fig. 2. Neurons are grouped in layers. Information from the environment is accepted by the neurons in the first, input layer. Outputs of all neurons in one layer are connected to all the inputs of neurons from the next layer, and the outputs of neurons in the last layer are actually outputs of the network. Layers containing neurons that are not in direct contact with the environment are hidden layers.

Information from the environment is brought to the inputs of the input neurons, and then processed by all neurons in the network. In this case, neurons in input and output layer are characterized by linear activation function and neurons in hidden layer are characterized by sigmoid activation function. In the process of the network training, the network parameters (connection weights and threshold activation function) should be determined so that difference between the desired response and actual response of the network is minimal. Determination of parameters is performed using an iterative optimization process. For the process of neural networks training presented in this paper, Quasi-Newton algorithm, which is a modification of backpropagation algorithm with higher order of convergence, is used [13].

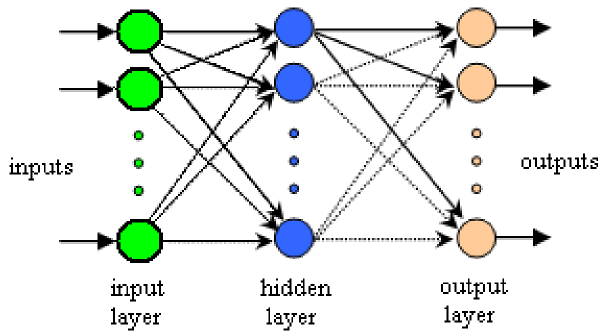

Fig. 2. MLP structure

A FTDNN is a special type of network, which consists of a feedforward MLP network having at the inputs, besides the input signal at the present moment, also the time-delayed values of the input signal [23]. FTDNN is a part of a general class of dynamic networks, called focused networks, in which the dynamics appear only at the input layer of a static multilayer feed-forward network.

The proposed FTDNN model for the detection of precipitation is shown in Fig. 3. It is defined by the following expression:

$$Q(t) = f(A(t), A(t-1), ..., A(t-n_u)) . \quad (9)$$

The value of the output variable that carries information about the appearance or absence of precipitation, $Q(t)$, depends on the current value of the signal attenuation, $A(t)$, calculated by using RSL [12], as well as on a series of past values of the signal attenuation, $A(t\text{-}1)$,…, $A(t\text{-}n_u)$, where n_u – is the number of input time-delays.

In this case, the number of neurons in the input layer is equal to the number of input time-delays increased by one ($n_u + 1$) and the number of neurons in the output layer is always equal to one. The number of hidden neurons cannot be a priori set and it is determined during the training by training and comparing networks with different number of hidden neurons.

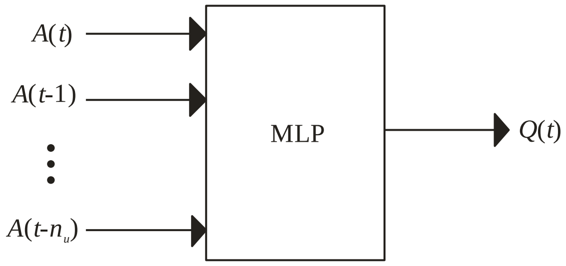

Fig. 3. The proposed neural model for detection of precipitation

IV. Numerical Results

Data used to train the neural networks were obtained at the link between Garmisch-Partenkirchen and Mount Wank, 4 km long, in the Alps, in the southern part of Germany, Fig. 4, in the period of 14 days, at the frequency of 18.7 GHz. The RSL recording was done every minute using a small storage device mounted on the towers with a resolution of less than 0.05 dB. This storage device (Cinterion TC65i) combined a Java virtual machine, two ADC (analog-to-digital converter) channels and a GSM module. The purpose of the Java virtual machine is to run adequate custom logging program. An ADC was used for the process of analog-to-digital conversation and its input was connected to the RSL monitoring voltage output of the link. Via the GSM module, the data was sent over the GSM network to the server for further processing. In order to deliver continuous data processing, the algorithm which is based on spectral analysis of time series was used [12]. Simplification of the analysis and processing of data was accomplished with the help of the database system. This database system consists of a MySQL backbone, which contains data tables. Besides RSL data, data tables also contain information about location, frequency and polarization of the microwave link, rain gauge data and meteorological data from weather station, which is located in Mount Wank. For the purpose of the parsing and exporting data to and from the database, python scripts were used.

Information contained in the test set, which is used for testing the networks, is also obtained on the same link, at the same frequency, in a period of 37 days.

In order to determine the network with the best performance, several neural networks with different number of input time-delays and different number of neurons in the hidden layer were tested. In this case, average test error (ATE) and correlation coefficient, r, [13] were used as the measure of quality of prediction.

Table I shows the results of testing of different neural networks with one hidden layer, where n is the number of neurons in the hidden layer. As can be seen from the Table I, the network with the best performance is a network with 10 input time delays and 10 neurons in the hidden layer (ANN13). This network was chosen as the final model and all further results refer to it.

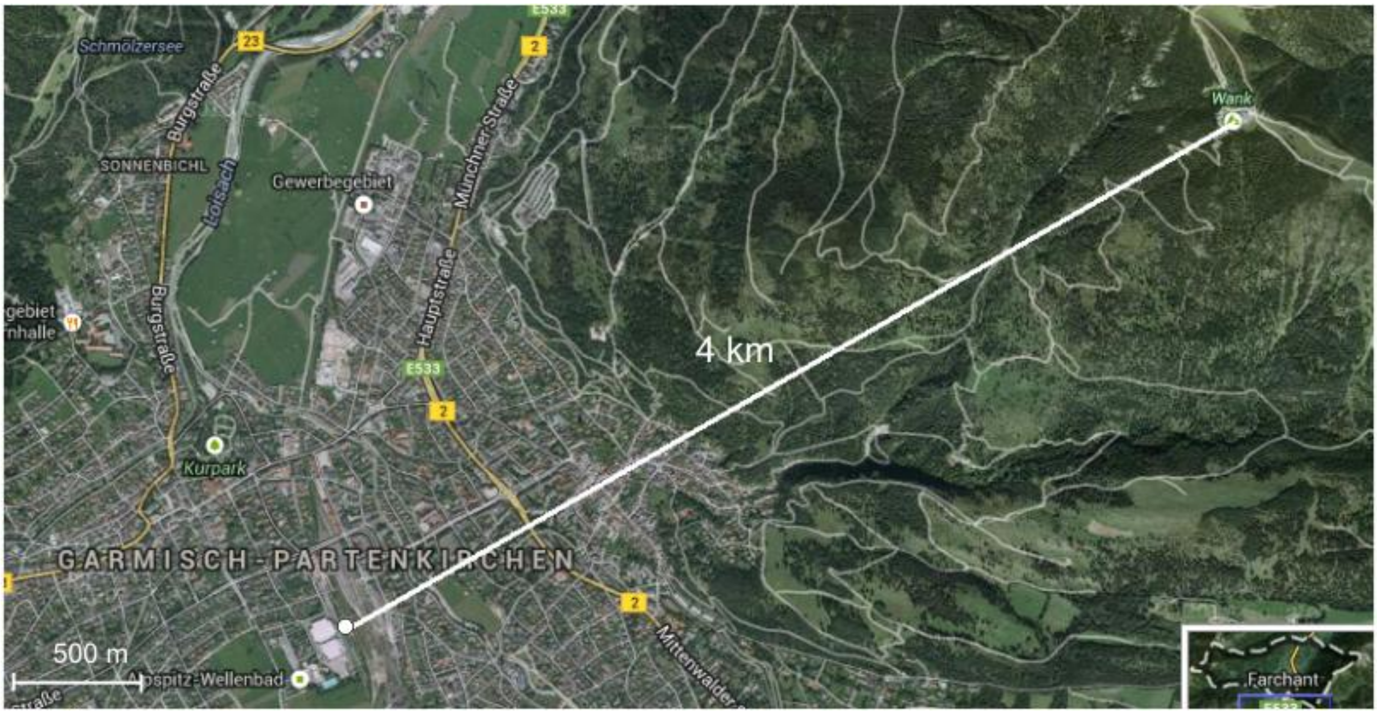

Fig. 4. Link between Garmisch-Partenkirchen and Mount Wank, 4 km long, in the Alps, in the southern part of Germany

TABLE I
TEST RESULTS

Neural network	n_u	n	ATE [%]	r
ANN1	1	10	1.4311	0.9536
ANN2	1	30	2.0288	0.9340
ANN3	1	50	3.5104	0.8850
ANN4	3	10	9.4000	0.6766
ANN5	3	30	9.7900	0.6615
ANN6	3	50	9.6100	0.6685
ANN7	5	10	1.9067	0.9379
ANN8	5	30	1.8089	0.9411
ANN9	5	50	3.5313	0.8839
ANN10	8	10	9.3600	0.6779
ANN11	8	30	9.4300	0.6752
ANN12	8	50	9.4800	0.6733
ANN13	10	10	1.1095	0.9647
ANN14	10	30	1.9012	0.9381
ANN15	10	50	4.2237	0.8606
ANN16	13	10	9.4600	0.6735
ANN17	13	30	10.1400	0.6476
ANN18	13	50	9.8400	0.6589
ANN19	15	10	8.5300	0.7081
ANN20	15	30	10.3200	0.6403
ANN21	15	50	10.6800	0.6263
ANN22	18	10	9.6300	0.6664
ANN23	18	30	9.6200	0.6670
ANN24	18	50	10.3300	0.6402

Fig. 5 illustrates the results of precipitation detection for a period of 37 days done by the method described in [12] (Fig. 5(a)) in comparison to the results obtained by the proposed neural model (Fig. 5(b)). It is important to note that the results refer to an RSL sequence not used for the model development.

As noted above, the variable Q carries information about the presence or absence of precipitation, i.e. it can takes only two values, 0 or 1, in certain points in time (the signal was sampled every minute). In other words, variable Q is a discrete-time and discrete-amplitude variable. The absolute error, shown in Fig. 5(c), is the absolute value of the difference between the variable Q obtained by the previous numerical method and the value of the variable Q obtained by the proposed neural model. Therefore, the obtained values of the absolute error indicate a wrong detection of precipitation in a certain point in time. If the value of the absolute error is equal to 1, a wrong detection of precipitation was made at that moment. Otherwise, if the value of the absolute error is equal to 0, an accurate detection of precipitation was made at that moment. To measure the quality of a neural model, it is more suitable to use the ATE. The obtained value for ATE of 1.1095%, actually means that, on average, each ninetieth value of absolute error is equal to 1 (i.e. each ninetieth value of the variable Q, which is obtained by using the neural model, is different from the one obtained by the numerical method), which can be considered as quite satisfactory.

As an additional illustration, Fig. 6 shows a part of the results shown in Fig. 5, for a period of 6 minutes during the first day, where the RSL is sampled every minute. Based on the values of the absolute error, shown in Fig. 6(c), it can be seen that accurate detection of precipitation was carried out in 5 of 6 points in time.

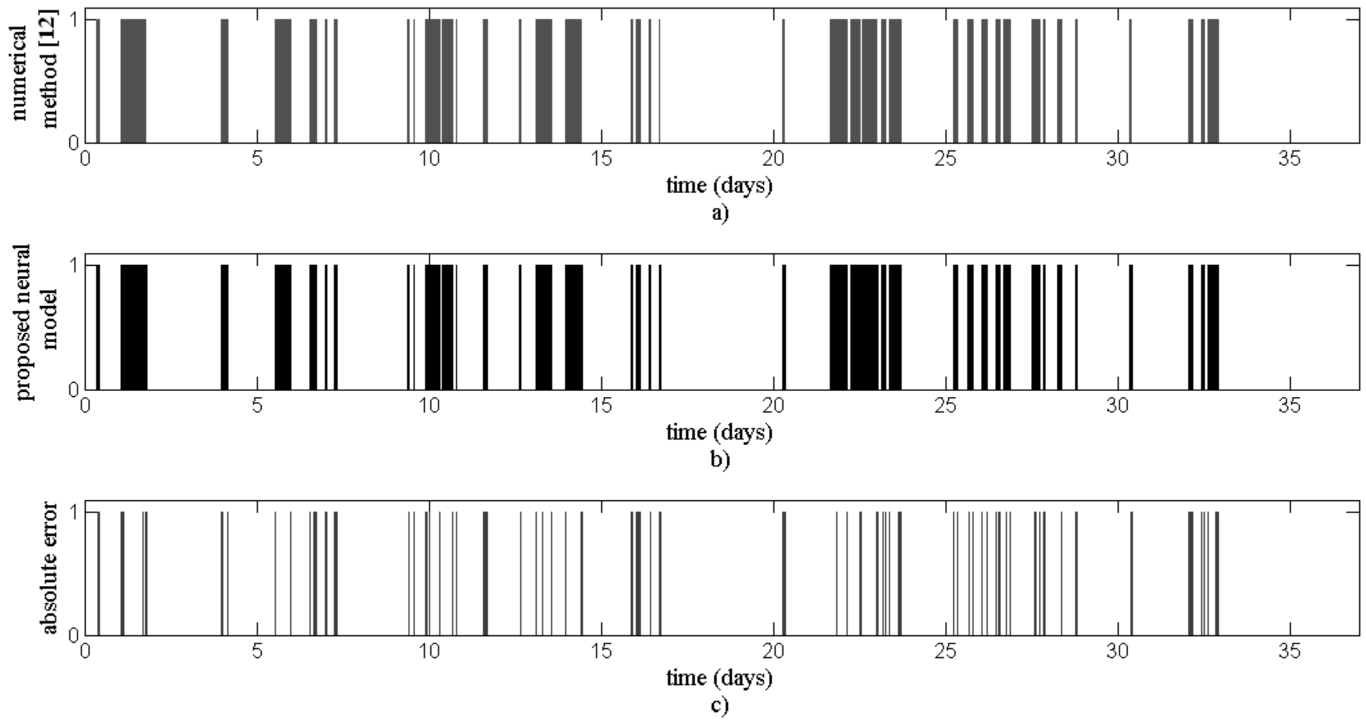

Fig. 5. a) Values of the variable *Q* obtained by the proposed method in [12], b) Values of the variable *Q* obtained by the proposed neural model, c) Absolute error

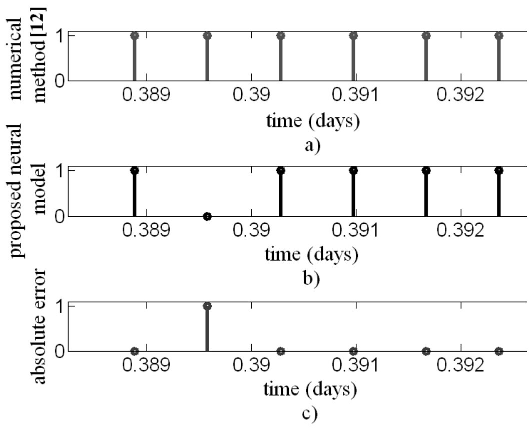

Fig. 6. a) Values of the variable *Q* obtained by the proposed method in [12], b) Values of the variable *Q* obtained by the proposed neural model, c) Absolute error

V. CONCLUSION

This paper presents development and validation of model for precipitation detection using focused time-delay neural networks. Precipitation detection was carried out based on the received signal level. For training and testing of the networks, the measured data obtained at the link between Garmisch-Partenkirchen and Mount Wank, and precipitation detection results using one of the previously proposed models, were used. Several neural networks with different number of input time-delays and different number of neurons in the hidden layer were trained and tested with the data obtained on the same link, but not used for model development. Selecting the network with the best performance was made based on the parameters that are used to determine the quality of the tested network response. Once the model is developed, the presence of the precipitation is determined by calculation of the neural network response for the RSL sequence, which is significantly faster than the previously proposed numerical method, making the process of the precipitation detection more efficient.

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REFERENCES

[1] J. Stratton, “The effect of rain and fog on the propagation of very short radio waves”, *P. IRE*, 18, 1064–1074, doi:10.1109/JRPROC.1930. 222101, 1930.

[2] G. Mueller, “Propagation of 6-millimeter waves”, *P. IRE*, 34, 181-183, doi:10.1109/JRPROC.1946.234240, 1946.

[3] D. Atlas, and C.W. Ulbrich, “Path-and area-integrated rainfall measurement by microwave attenuation in the 1–3 cm band”, *J. Appl. Meteorol.*, 16, 1322–1331, 1977.

[4] A. Holt, G. Kuznetsov, and A. Rahimi, “Comparison of the use of dual-frequency and single-frequency attenuation for the measurement of path-averaged rainfall along a microwave link”, *IET Microw. Antenna P.*, 150, 315–20, doi:10.1049/ipmap: 20030616, 2003.

[5] A.R. Rahimi, G.J.G. Upton, and A.R. Holt, “Dual-frequency links-a complement to gauges and radar for the measurement of rain”, *J. Hydrol.*, 288, 3–12, doi:10.1016/j.jhydrol.2003.11.008, 2004.

[6] H. Minda, and K. Nakamura, “High temporal resolution pathaverage rain gauge with 50-GHz band microwave”, *J. Atmos. Ocean. Tech.*, 22, 165–179, 2005.

[7] G. Upton, A. Holt, R. Cummings, A. Rahimi, and J. Goddard, “Microwave links: the future for urban rainfall measurement?”, *Atmos. Res.*, 77, 300–312, doi:10.1016/j.atmosres.2004.10.009, 2005.

[8] H. Leijnse, R. Uijlenhoet, and J.N.M. Stricker, “Hydrometeorological application of a microwave link: 2. Precipitation”, *Water Resour. Res.*, 43, W04417, doi:10.1029/2006 WR004989, 2007a.

[9] H. Messer, A. Zinevich, and P. Alpert, “Environmental monitoring by wireless communication networks”, *Science*, 312, 5774, doi:10.1126/science.1120034, 2006.

[10] H. Leijnse, R. Uijlenhoet, and J.N.M. Stricker, “Rainfall measurement using radio links from cellular communication networks”, *Water Resour. Res.*, 43, W03201, doi:10.1029/2006 WR005631, 2007b.

[11] M. Schleiss, and A. Berne, “Identification of dry and rainy periods using telecommunication microwave links”, *IEEE Geosci. Remote S.*, 7, 611-615, doi: 10.1109/LGRS.2010. 2043052, 2010.

[12] C. Chwala, A. Gmeiner, W. Qiu, S. Hipp, D. Nienaber, U. Siart, T.Eibert M. Pohl, J. Seltmann, J. Fritz and H. Kunstmann, ”Precipitation observation using backhaul links in the alpine and pre-alpine region of Southern Germany”, *Hydrol. Earth Syst. Sci. Discuss*, Januar, 2012.

[13] Q.J. Zhang, K.C. Gupta, *Neural Netvorks for RF and Microwave Design*, Artech House, 2000.

[14] F. Giannini, G. Leuzzi, G. Orengo, and M. Albertini, “Small-signal and large-signal modeling of active devices using CAD-optimized neural networks,” *Int. J. RF Microw. Comput.-Aided Eng.*, vol. 12, pp. 71-78, Jan 2002.

[15] Q.J. Zhang, K.C. Gupta, and V.K. Devabhaktuni, “Artificial neural networks for RF and microwave design—From theory to practice,” *IEEE Trans. Microw. Theory Tech.*, vol. 51, no. 4, pp. 1339–1350, Apr. 2003.

[16] Z. Marinković and V. Marković, “Temperature dependent models of low-noise microwave transistors based on neural networks,” *Int. J. RF Microw. Comput.-Aided Eng.*, vol. 15, no. 6, pp. 567-577, Nov. 2005.

[17] Z. Marinković, O. Pronić, and V. Marković, “Bias-dependent scalable modeling of microwave FETs based on artificial neural networks,” *Microw. Opt. Techn. Lett.*, vol. 48, pp. 1932-1936, Oct 2006.

[18] J.E. Rayas-Sanchez, “EM-based optimization of microwave circuits using artificial neural networks: The state-of-the-art,” *IEEE Trans. Microw.Theory Tech.*, vol. 52, no. 1, pp. 420–435, Jan. 2004.

[19] H. Kabir, L. Zhang, M. Yu, P. Aaen, J. Wood, and Q.J. Zhang “Smart modeling of microwave devices,” *IEEE Microw. Mag.*, vol. 11, pp.105–108, May 2010.

[20] Z. Marinković, G. Crupi, D.M.M.-P. Schreurs, A. Caddemi, and V. Marković, “Microwave FinFET Modeling based on Artificial Neural Networks Including Lossy Silicon Substrate,” *Microelectron Eng.*, vol. 88, no. 10, pp. 3158–3163, Oct. 2011.

[21] M. Agatonović, Z. Marinković, and V. Marković, “Application of ANNs in evaluation of microwave pyramidal absorber performance,” *Appl. Comput. Electrom.*, vol. 27, no. 4, pp. 326-333, Apr. 2012.

[22] Z. Marinković, O. Pronić-Rančić, V. Marković, “Small-signal and noise modelling of class of HEMTs Using Knowledge-Based Artificial Neural Networks,” *Int. J. RF Microw. Comput.-Aided Eng.*, vol. 23, no. 1, pp. 34-39, Jan. 2013.

[23] “Focused Time-Delay Neural Network”, *MathWorks*, http://www.mathworks.com/help/nnet/ug/focused-time-delay-neural-network-timedelaynet.html.