An Antenna Pattern Deconvolution Method to Extract Input Parameters Based on the RET Theory

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Abstract

The influence of vegetation on radiowave signals has become an important aspect of the design of wireless communication links. In recent years the theory of Radiative Energy Transfer (RET) has been adopted as a reliable tool to predict the radiowave propagation through and near vegetation. The developed RET prediction model requires 4 independent input parameters, which so far had to be established from one measurement only, thus limiting their accuracy. An independent measurement which is termed the phase function can readily yield 2 of the 4 input parameters independently, which significantly increases the accuracy of these parameters. However one major factor influencing the phase function measurement is the radiation pattern of the receiver antenna. The measured pattern will be the result of the convolution of the antenna radiation pattern and the phase function of the vegetation medium. The measured pattern therefore needs to undergo a deconvolution process before any RET input parameters can be derived from it. This paper presents the deconvolution method developed using optimum compensation deconvolution. A pre-filtering technique using auto/cross-correlation is utilized to improve the deconvolution results, as well as error function is used to determine the optimal value of the iterative filter parameter.

1 Introduction

Accurate prediction models are vital for planning and managing the radio spectrum in the light of a constantly increasing demand for wireless communications services. The influence of vegetation on the radio path has long been recognised as one of the most difficult modelling challenges. The theory of Radiative Energy Transfer (RET) provides a full wave solution for vegetation modelling and has successfully been adopted for modelling of propagation in the presence of vegetation at microwave and millimeter wave frequency [1, 2]. To accurately model radiowave propagation in the presence of vegetation, the RET requires a set of 4 input parameters. These depend on factors such as frequency, type of vegetation, state of foliation etc. and need to be determined experimentally.

In previous implementations of the RET, all 4 parameters were determined using one type of measurement only, namely the signal attenuation with vegetation depth [2]. The accuracy that can be achieved by this approach is however limited. Two of the four RET input parameters are also present in the description of the vegetation scatter function in the RET, the so called phase function [2]. Determination of the phase function through a separate set of measurements will yield these 2 input parameters independently and therefore all 4 parameters can be established far more accurately.

However the result of the phase function measurement is highly depended on the receiver antenna radiation pattern. The measured signal pattern is the convolution product of the phase function and the receiver antenna radiation pattern. A deconvolution application has therefore to be applied to remove the influence of the receiver antenna radiation pattern.
Although deconvolution techniques are widely used in areas like astronomy and image processing [3], they have so far only found limited application in radiowave propagation. Deconvolution is not a linear and not always a straightforward operation.

This paper introduces the application of an optimum compensation deconvolution technique for the purpose of restoring the phase function from a measured pattern under consideration of the antenna radiation pattern. The paper is outlined as follows. Section 2 briefly summarises the relevant parts of the theory of Radiative Energy Transfer. Section 3 shows how antenna radiation pattern and phase function convolve to produce the measured signal pattern and briefly highlight why straightforward deconvolution may not provide the correct answers. In section 4 the optimum compensation filtering is introduced and the derived deconvolution process is demonstrated using computer generated data which includes the influence of white noise. Section 5 provides a brief description of the measurement scenario for data obtained from vegetation measurements in a controlled indoor environment. Section 6 gives preliminary results after deconvolution has been applied to the measured signal pattern and presents the Bennia-Riad criterion for further optimization. In section 7 a feasible pre-filtering technique using the auto- and cross-correlation is presented, which improves deconvolution results. In section 8 an error function criterion is used to determine the optimal parameter in the optimum compensation filter. Finally, restored phase function pattern and extracted values of parameters and are given. Concluding remarks are found in section 9.

2 Introduction to the RET and its phase function

The RET theory simulates the vegetation medium as a homogeneous environment consisting of randomly distributed scatterers . This model can be represented by a set of parameters: , the absorption coefficient, , the scattering coefficient, the ratio between the forward lobe and the total scattered power, and the beamwidth of the forward lobe [1, 2]. The scalar form of the fundamental RET equation is given by follows:

\[
\frac{dI}{ds} = -(\sigma_a + \sigma_s) \cdot I + \sigma_s \int \hat{s}_1, \hat{s}_2' \cdot I \cdot d\Omega
\]

(1)

where denotes the specific signal intensity, and \( p(\hat{s}_1, \hat{s}_2') \) is the phase function, with \( \hat{s}_1 \) and \( \hat{s}_2' \) representing the directions of the radio waves entering and emanating from each other respectively, and \( \Omega \) is the solid angle over all spatial directions \( \hat{s}_2' \). The phase function can be modeled as a Gaussian forward lobe and an isotropic back scatter outside the main lobe [1]. Fig. 1 demonstrates the variation of the phase function pattern as varying beamwidths in 2-dimension, i.e. the horizontal plane.

The phase function is given by:

\[
p(\theta) = \alpha q(\theta) + (1 - \alpha)
\]

(2)
where $\theta$ represents the rotation angle of the receiver antenna in degrees. In the context, the beamwidth of a Gaussian antenna pattern and the traditionally used Half Power Beamwidth (HPBW) are related by [1]:

$$\beta = 0.6 \cdot \beta_{-3dB}$$ (4)

3 Influence of antenna radiation pattern and deconvolution ill-posedness

In the transport theory, it is assumed that the various scattered wave trains are uncorrelated in phase [1]. Hence the power can be added in real quantities at the receiver side. The radiation pattern of a typical antenna, however, is not an ideal pulse but a curve comprised of a mainlobe and a significant amount of sidelobes. While placing the receiver antenna inside the vegetation, both its mainlobe and sidelobes are receiving signals from rays both being directly transmitted from the transmitter and scattered from all the trees surrounding the receiving antenna.

This can be geometrically depicted as shown in Fig. 2 and its strength can be mathematically calculated as the weighted sum of all directional contributions [4] and given as:

$$p_{RX}(\theta_{RX}) = \sum_{\theta_j} i(\theta_j) g_{RX}(\theta_j - \theta_{RX})$$

(5)

where $p_{RX}$ is the measured power strength, $g_{RX}$ is the radiation pattern of the receiver antenna. $\theta_{RX}$ and $\theta_j$ respectively represent the directions of the antenna mainlobe and an individual incident wave $j$, $j = 1, 2, \cdots n$. Their values are with respect to the same horizontal reference angle. $i$ denotes the density of the transmitted power just before reaching the receiver antenna, its distribution depends on the vegetation media only, and is therefore not related to the receiver antenna.

The discrete expression Eq. 5 shows that the measured power $p_{RX}$ is a convolution product between the receiver radiation pattern $g_{RX}$ and the incident wave density, $i$:

$$p_{RX}(\theta) = i(\theta) \ast g_{RX}(\theta)$$

(6)

According to the convolution theorem, convolution in the original domain is equivalent to multiplication in the transform domain:

$$P_{RX}(\omega) = I(\omega) G_{RX}(\omega)$$

(7)

where $P_{RX}$, $I$ and $G_{RX}$ are the Fourier Transform of $p_{RX}$, $i$, and $g_{RX}$ respectively; $\omega$ is the variable in the transform domain corresponding to $\theta$ in the original domain.
Eq. 7 suggests that a straightforward solution of the deconvolution can be achieved by inverse Fourier Transform of $I(\omega)$, which would be the result of division of $P_{RX}(\omega)$ over $G_{RX}(\omega)$, i.e. $I(\omega) = \frac{P_{RX}(\omega)}{G_{RX}(\omega)}$. However, the presence of random noise in the signal and the resolution limits of the computer processing can generate large spike errors in the division. These errors can consequently swamp most of the useful information contained in $i(\theta)$ after inverse Fourier Transform. This is known as the ill-posed problem [5].

4 Deconvolution by optimum compensation filtering

Due to the ill-posed problem, accurate deconvolution cannot be undertaken by division in the transform domain. $P_{RX}$ needs to undergo suitable filtering, $F(\omega)$, to produce the optimal estimate $I_e(\omega)$ of $I(\omega)$.

$$I_e(\omega) = P_{RX}(\omega)F(\omega)$$ (8)

The optimum compensation filtering deconvolution is documented by S. M. Riad et al. in [6]. Two criteria are deployed to iteratively determine the optimization filter.

1. Minimum mean-square-error (MMSE) criterion:

$$E_1 = \int_{-B}^{B} |I_e(\omega) - I(\omega)|^2 d\omega$$ (9)

$$I_e(\omega) = \begin{cases} P_{RX}(\omega) \cdot F(\omega) & \text{for } |\omega| \leq B \\ 0 & \text{for } |\omega| > B \end{cases}$$ (10)

where $B$ represents the band limit of the signal in the transform domain. The consistence of $I_e(\omega)$ and $I(\omega)$ is guaranteed when finding the minimum of $E_1$. The resultant minimum is equivalent to $F(\omega) = \frac{1}{G_{RX}(\omega)}$, but the ill-posed problem still exists in this case.

2. Errors-control criterion:

$$E_2 = \int_{-B}^{B} |I(\omega)F(\omega)|^2 d\omega$$ (11)

where the filter $F(\omega)$ is used to control the spike-like errors generated by the straightforward division.

The two criteria can be conveniently grouped into one [7]:

$$E = E_1 + \lambda E_2$$ (12)

$$E = \int_{-B}^{B} |I_e(\omega) - I(\omega)|^2 d\omega + \lambda \int_{-B}^{B} |I(\omega)F(\omega)|^2 d\omega$$

where $\lambda$ is the optimization parameter, which is iteratively determined based on a compromise between signal consistency and noise minimization. The optimum compensation filter $F(\omega)$ can be obtained by setting the partial derivatives equal to zero with respect to the real and imaginary parts respectively [6].

$$F(\omega) = \frac{G_{RX}(\omega)}{|G_{RX}(\omega)|^2 + \lambda}$$ (13)

where in Eq. 13 the superscript * denotes complex conjugate. The optimum compensation filter, $F(\omega)$, represents a form of the Wiener filter.

To develop, optimize and subsequently verify this optimum compensation filter technique, two computer-generated patterns, one representing the phase function and the other representing the Gaussian horn antenna radiation pattern, are used to generate data similar to the values experienced in measurement data. Additive white Gaussian noise is added. The SNR can be controlled and is set to around 20 dB in the example illustrated in Fig. 3.
Figure 3: (a) Computer-generated idealized patterns and (b) their convolution pattern with added noise.

Figure 4: Restored patterns from: (a) direct division deconvolution; (b) under-compensated deconvolution; (c) optimum compensation deconvolution; (d) over-compensated deconvolution.
Fig. 4 illustrates 4 examples of signal restoration by deconvolution. Fig. 4a shows the deconvolution result by straightforward division in transform domain. The true information of signal in the original domain is entirely swamped by noise. Fig. 4c demonstrates the deconvolution result using the optimum compensation filtering, where the parameter $\lambda$ has been chosen correctly. The original computer-generated phase function pattern is overlaid for comparison, the 2 curves are overall coincident. Figs. 4b and 4d show the so called under- and over-compensated cases respectively, where the optimum filtering parameter $\lambda$ has either been chosen too small (Fig. 4b) or too large (Fig. 4d). In this example computer-generated patterns are used so the true information is available and can be used as reference to assess the restoration quality.

Eqs. 8 - 13 show that, if $P_{RX}(\omega)$ and $G_{RX}(\omega)$ are known, the optimal filter $F(\omega)$ will be available by Eq. 13 once the optimal parameter $\lambda$ is determined, and consequently $I_e(\omega)$ can be calculated by Eq. 8. Hence the Fourier transforms of the receiver antenna radiation pattern and the measured output pattern, i.e. $G_{RX}(\omega)$ and $P_{RX}(\omega)$, need to be known to attain $I_e(\omega)$. In practice, the non-transformed functions, $g_{RX}(\theta)$ and $p_{RX}(\theta)$, are measured.

5 Anechoic chamber measurement

Measurements were conducted in a controlled indoor environment (anechoic chamber), which has an interior physical size of $5.60\text{m} \times 2.25\text{m} \times 2.40\text{m}$. The transmitter uses a $10\text{dBi}$ standard gain horn antenna and at the receiver side a Gaussian horn of $20\text{dBi}$ gain at $20\text{GHz}$ is used. The distance between the transmitter and the receiver is sufficiently large to ensure the far-field conditions.

The phase function measurement was conducted using 16 Ficus trees to form a small scale vegetation body representing a miniature forest. The receiver antenna was placed at different vegetation depths as shown in Fig. 5 and rotated around its own vertical axis at each position. The measured received signal levels at positions 1, 2, and 3 with rotation angle are shown in Fig. 6a. The maximum signal occurs when the antennas are boresight (azimuth angle $\theta = 0$). A decrease of signal level of nearly $10\text{dB}$ can also be observed between position 1 and 2, further reduction of signal level, $16\text{dB}$, between position 2 and 3. The measurement of the Gaussian horn radiation pattern was conducted in the absence of vegetation as shown in Fig. 6b.

6 Preliminary deconvolution results from measurement

The measured data sets of $p_{RX}(\theta)$ and $g_{RX}(\theta)$ are transformed by Fourier Transform to give $P_{RX}(\omega)$ and $G_{RX}(\omega)$. The measured values of $p_{RX}(\theta)$ and $g_{RX}(\theta)$ are both affected by noise. The noise can reasonably be assumed to be random, mean-zero, white noise.

In the case when using computer-generated input data, it is possible to determine the optimum compensation filter parameter $\lambda$ by minimizing the error between the deconvolution result for $p_{RX}(\theta)$ and the original computer-generated input function as described in section 4. Unlike in the simulation the phase function pattern cannot be determined from measurements other than by deconvolution.

Hence a different method needs to be found to yield the parameter for the optimum compensation filter. The Bennia-Riad criterion [6] provides a quantitative measure of the filter taking into account the noise reduction and the filtration error. This is achieved by partitioning the transfer function of the phase function pattern in the transform domain into a passband, in which the SNR is large, and a stopband, with small SNR. The partition follows the conventional Half Power criterion. The transfer function of most practical applications is best represented by a low pass filter [3]. The aim is to describe the low pass filter so that the useful information mainly falls into the passband, whereas the stopband contains little information but has high noise content.

The deconvolution is optimal when it manages to restore the useful information in the signal, while minimizing the effects of noise. The Bennia-Riad criterion is used for the iterative deconvolution process presented here. It minimizes the $\text{rms}$ error between $I(\omega) = \frac{P_{RX}(\omega)}{G_{RX}(\omega)}$ and iteration $I^\lambda_e(\omega)$ as a function of the optimization parameter $\lambda$ [7]:

$$\sigma_n(\lambda) = \text{rms} \left\{ \left| I^\lambda_e(\omega) - I(\omega) \right| \right\}$$

where $n$ denotes number of iteration; $\text{rms}$ represents the root mean squared operation performed on the quantity inside the brackets $\{ \}$ over both pass- and stop-band in the transform domain. $I^\lambda_e(\omega)$ represents an estimate of the transfer function in the transform domain after filtering and $I(\omega)$ is the transfer function obtained by straightforward division $\frac{P_{RX}(\omega)}{G_{RX}(\omega)}$, which
Figure 5: Measurement geometry in the presence of vegetation.

Figure 6: Measured (a) signal patterns at positions 1, 2 and 3 and (b) radiation pattern of the receiver antenna.
Fig. 7: $rms$ error values calculated in the passband and stopband.

is the case when $\lambda = 0$.

To recover useful information, the optimal estimate, $I_{\lambda}(\omega)$, in the passband should be as close as possible to the value of $I(\omega)$, while as different as possible in the stopband. Fig. 7 illustrates the calculated $rms$ error value in the passband and the stopband respectively. The magnitude of the $rms$ error was normalized with respect to its maximum within the corresponding interval band. The abscissa is the value of the optimal parameter $\lambda$ expressed in dB. The range of $\lambda$ is chosen to be relatively wide from $-80\, dB$ to $+60\, dB$ covering all experienced values.

The chosen optimal parameter $\lambda$ according to the criterion discussed above falls into the range of $-30\, dB$ to $+10\, dB$. Here the value of $rms$ error in the passband is close to zero, therefore guarantees a high degree of similarity of the optimal estimate $I_{\lambda}(\omega)$ and $I(\omega)$ whereas in the stopband the $rms$ error approaching the unity, consequently ensuring noise content reduction. The two extremes to either side of the $\lambda$ range are:

- Under-compensated restoration: value of the parameter $\lambda$ is chosen to be less than $-60\, dB$. This indicates the estimate $I_{\lambda}(\omega)$ coincides with $I(\omega)$ not only in the passband but also in the stopband. Consequently, the high noise contents still remains, this is the ill-posedness.

- Over-compensated restoration: value of the parameter $\lambda$ is chosen more than $+40\, dB$. This means that too much distortion occurs in both bands, therefore too much of the useful information is lost after filtering although noise has been greatly reduced.

Fig. 8 shows the restoration results in original domain under three conditions described above: the top curve Fig. 8a is obtained by optimum compensation filtering, where the parameter $\lambda$ has been correctly chosen as $-5\, dB$. The envelop of this graph shows a Gaussian shape, indicating correct retrieval of the useful information. The smoothness of the curve indicates sufficient noise reduction. Fig. 8b illustrates a case of under-compensation restoration, where the chosen value of parameter $\lambda$ is too small at $-60\, dB$. The restored graph still contains a significant amount of noise, and the information part of signal appears distorted. Fig. 8c demonstrates the over-compensated case, with parameter $\lambda$ value too large at $+40\, dB$. It shows the curve extremely smooth and the noise has been completely eliminated. However, considerable detailed characteristics of the original signal have also been removed.

7 Pre-filtering improvement

Examining both the measured antenna radiation patterns and the measured directional spectra curves it is apparent that both are not particularly smooth curves. Their rapid amplitude variation with rotation angle can be considered a form of noise content. Reducing this noise content without losing too much of the overall information in the signal curves prior to deconvolution will therefore be advantageous for the performance of the deconvolution process and the quality of the recovered patterns. The pre-filtering technique found to be useful in this context is the auto/cross-correlation.

8
To apply pre-filtering both sides of Eq. 6 are convolved with the same expression. The expression used is the antenna radiation pattern, which has been reversed in direction around rotation angle $\theta = 0$, i.e. $g_{RX}(-\theta)$. Convolution of both sides of Eq. 6 in the original domain with $g_{RX}(-\theta)$ yields:

$$i(\theta) * (g_{RX}(\theta) * g_{RX}(-\theta)) = p_{RX}(\theta) * g_{RX}(-\theta)$$  \hspace{1cm} (15)

The LHS contains the auto-correlation $g_{RX}(\theta) * g_{RX}(-\theta)$, whereas the RHS presents the cross-correlation $p_{RX}(\theta) * g_{RX}(-\theta)$. This operation does not affect the phase function pattern $i(\theta)$, hence there is no loss of information. The Fourier Transform of Eq.15 results in:

$$I(\omega) (G_{RX}(\omega)G_{RX}^{*}(\omega)) = P_{RX}(\omega)G_{RX}^{*}(\omega)$$ \hspace{1cm} (16)

Fig. 9a shows the application of the auto-correlation pre-filter applied to the measured antenna radiation pattern of the 20 dBi Gaussian horn antenna at 20 GHz. Fig. 9b demonstrates the cross-correlation pre-filter applied to the correspondingly measured re-radiation pattern recorded at 20 GHz. The new patterns of $g_{RX}(\theta) * g_{RX}(-\theta)$ and $p_{RX}(\theta) * g_{RX}(-\theta)$ have become much smoother curves, which is advantageous for the deconvolution operation.

In addition the auto- and cross-correlation pre-filtering technique helps convergence and provides noise reduction. The expression $G_{RX}(\omega)G_{RX}^{*}(\omega)$ in Eq.16 will always be positive, this ensures convergence of the iterative transform domain methods while also increasing the rate of convergence [8, 9, 10, 11]. Furthermore, random noise on the measurements will be significantly reduced as demonstrated by the now much smoother patterns in Fig.9. The cross-correlation of $p_{RX}(\theta) * g_{RX}(-\theta)$ will reduce the effect of random signal fluctuations between the two patterns and hence provide a noise reduction yielding better deconvolution results. The auto-correlation of the LHS of Eq.15 will in effect make the resulting pattern from the antenna radiation measurement symmetrical with respect to $\theta = 0$, which also improves deconvolution results.
Figure 9: Pre-filtering on the measurement patterns using (a) auto-correlation of the antenna radiation pattern and (b) cross-correlation of the measured directional spectrum.
8 Determination of optimal parameter using error function

The optimal value of parameter $\lambda$ should be located in the range determined by the Bennia-Riad criteria described in section 6. An error function is used to determine its optimal value. Definition of the error function in the original domain is given by [8]:

$$e(\theta) = p_{RX}(\theta) - i_e(\theta) * g_{RX}(\theta)$$  \hspace{1cm} (17)

where $p_{RX}(\theta)$ represents the measurement pattern, $g_{RX}(\theta)$ denotes the Gaussian horn radiation pattern and $i_e(\theta)$ represents the deconvolution pattern, i.e. the best restoration of $i(\theta)$. The error function must be carefully interpreted. Two parameters are used for its characteristics: the mean value $\bar{e}$ and the standard deviation $\xi$. The mean value is given by

$$\bar{e} = \frac{1}{N} \sum_{k=1}^{N} e(\theta)$$  \hspace{1cm} (18)

where $N$ denotes the number of measurement samples. Ideally $\bar{e}$ should be zero, therefore the absolute value of $\bar{e}$ needs to be minimized. The standard deviation, $\xi$, is given by:

$$\xi = \left[ \frac{1}{N} \sum_{k=1}^{N} (e(k) - \bar{e})^2 \right]^{1/2}$$  \hspace{1cm} (19)

Fig. 10a shows the calculated standard deviation values of the error function using Eq. 19. Its minimum happens at $\lambda_1 = -6.26\,dB$. Fig. 10b represents the calculated mean values of the error function using Eq. 18. Its absolute minimum occurs at $\lambda_2 = 12.67\,dB$. $\lambda_1$ and $\lambda_2$ are substituted into Eq. 13, then Eq. 8 is used, as well as the pre-filtering technique and inverse Fourier Transform to obtain the deconvolution results $i_e$. The top of Fig. 11 shows the convolution between the deconvolution restoration $i_e(\theta)$ with $\lambda_1 = -6.26\,dB$ and the Gaussian horn radiation pattern after applying auto-correlation in the original domain. The measurement pattern after pre-filtering is overlaid for comparison. The corresponding error function between the two patterns is shown at the bottom of this figure. Fig. 12 shows the convolution pattern and corresponding error function with parameter $\lambda_2 = 12.67\,dB$.

Closer examination of Fig. 13 indicates that the choice with $\lambda_2 = 12.67\,dB$ provides smaller values in the error function and less fluctuation than $\lambda_1 = -6.26\,dB$. This means that the restoration, after convolving with the pre-filtered Gaussian horn radiation pattern, resembles the measurement pattern more closely when using $\lambda_2 = 12.67\,dB$ than using $\lambda_1 = -6.26\,dB$. Hence, $12.67\,dB$ is a better choice for parameter $\lambda$ than $-6.26\,dB$ although it is just outside the optimal range, $-30\,dB$ to $+10\,dB$ determined by the Bennia-Riad criteria and hence a bit on the over-compensation side.

The restoration pattern after deconvolution is shown in Fig. 14 with extracted input parameters $\alpha = 0.96$ and $\beta = 22.5^\circ$. 

Figure 10: Calculated (a) the standard deviation and (b) the mean value of the error function.
Figure 11: Convolution pattern with $\lambda_1 = -6.26 \text{ dB}$ and corresponding error function.

Figure 12: Convolution pattern with $\lambda_2 = 12.67 \text{ dB}$ and corresponding error function.
Figure 13: Comparison of error functions of restoration patterns corresponding to $\lambda_1 = -6.26\, dB$ and $\lambda_2 = 12.67\, dB$.

Figure 14: Demonstration of the optimum compensation deconvolution result, $\lambda = 12.67\, dB$. 

For comparison, the measured pattern and the pre-filtered pattern are overlaid. It is evident that the deconvolution pattern preserves useful information, or fluctuation, as well as significantly eliminates random noise.

9 Conclusion

This paper demonstrates an improved technique to extract the input parameters of the RET theory from measurement data. To the author's knowledge the paper documents the first implementation of deconvolution techniques on antenna radiation pattern affected amplitude only measurement data. The paper briefly summarises the relevant parts of the RET theory and then concentrates on deconvolution. Implementation of the iterative optimum compensation deconvolution is demonstrated with computer-generated patterns. Determination of the optimal range for parameter by the Bennia-Riad criterion is demonstrated. Then pre-filtering using auto- and cross-correlation is introduced to improve deconvolution. An error function criterion using mean value and standard deviation is deployed to determine the best choice of parameter. This paper shows a successful extension of the application of the optimum compensation filtering technique to a measured RET phase function pattern distorted by the receiver antenna radiation pattern.

References


