# **Rain Events Detection using Energy Variation of Commercial Microwave Links Attenuation**

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Abstract: In this study, we propose a new method for detecting wet periods by using telecommunications Commercial Microwave Links (CML). The purpose of the study is to automatically find rain time slots. The attenuation of the microwave signal, propagating between a transmitting antenna and a receiving one, due to the variations of the climatic conditions over the link, is a non-stationary signal. When a rain event occurs over a CML, the attenuation signal level increases proportionally to the rain amount. This level decreases again at the end of the rain. These abrupt variations are exploited here to detect rainy time slots. The proposed method consists in splitting the attenuation signal into frames and computing the variation of the energy between consecutive frames. To determine whether the current frame corresponds to a wet period, the proposed method, named Energy Variation (EVA), compares the variation of the energy with a given threshold, while taking into account the status of the previous frame. Simulation results from real attenuation data of the mobile phone operator Telecel Faso SA (Burkina Faso) show that the proposed method allows the detection of 84.61% of rainy events. The Matthews Correlation Coefficient (MCC) is higher than 0.9, which demonstrates that EVA can discriminate between wet and dry periods with high accuracy.

**Keywords:** Commercial Microwave Link, Wet-Dry Classification, Energy, Attenuation, Rainfall

## Introduction

The microwave signal propagating between a transmitting and a receiving antenna loses power due to propagation, gases, and side effects (ITU-R, Rec P.525-4, 2019a; ITU-R, Rec P.676-12, 2019b). When this signal encounters a rain cell on its path, it undergoes additional attenuation due to the rain ITU-R, Rec P.838-3, 2005). Several works have shown that the knowledge of this additional attenuation can be used to estimate the amount of rainfall on the (Chwala and Kunstmann, 2019, David *et al.*, 2013, Doumounia *et al.*, 2014, Messer *et al.*, 2006).

The first step in the process of rain amount estimation, using a commercial microwave link, consists in identifying wet periods. Several methods have been proposed in the literature to address the problem of wet and dry periods classification. Schleiss and Berne (2010) proposed a method that exploits the standard deviation of the attenuation signal over sliding windows. This method, which we will refer to as "Moving Standard Deviation (MSD)", compares the standard deviation value computed for each frame to a predefined threshold. The weakness of this method lies in determining a suitable threshold, especially when the attenuation signal fluctuates during dry periods. Another wet/dry classification method was proposed by Chwala et al. (2012). This latter method exploits the spectrogram of the attenuation signal, finding that the power spectral density of the attenuation signal at low frequency during wet periods shows a significant deviation from the average spectrum during dry periods. The measurement of this deviation is used to detect wet periods. Polz et al. (2020) explored Convolutional Neural Networks (CNN) to detect the presence of rain. They consider the detection of rain events as a binary



classification problem. This approach requires a lot of data for training and testing the neural network. Cherkassky et al. (2014) proposed a classification tree exploiting the physical characteristics of precipitations to distinguish different precipitation types such as rain and sleet. Another method for detecting wet periods using the Pearson correlation coefficient was presented in (Rahimi et al., 2003). It exploits the fact that the correlation coefficient of the attenuation signals of double links connecting the same sites and transmitting at different frequencies is relatively high in wet periods. The disadvantage of this method is that it requires a double link. Finally, one can mention the wet/dry periods classification method proposed by Song et al. (2020). It is based on the Support Vector Machine (SVM) classification technique and uses the minimum, average and maximum values of the CML signal attenuation as statistical parameters for classification.

In this study, we propose a new method for detecting wet periods, using the variation of the attenuation signal energy between consecutive frames. When rain occurs on a given link on which a microwave propagates, the wave attenuation level increases proportionally to the rain amount. This attenuation level decreases again at the end of the rain. Thus, the quantification of this energy variation and the knowledge of the status of the previous frame allows us to determine the status of the current frame.

The remainder of this study is organized as follows: First, we describe the proposed new method for detecting wet periods. Then we present and discuss the results on actual attenuation data from the mobile phone operator Telecel Faso network (in Burkina Faso). We end this study with conclusions and perspectives.

## **Materials and Methods**

## Description of the Data

The data used in this study were obtained from a system that in real-time collects the power levels of the commercial microwave links of the mobile phone operator Telecel Faso (Burkina Faso). This system is installed in LAboratoire de Matériaux et Environnement (LA.ME) of the Joseph KI-ZERBO University, in Burkina Faso. Four links of the Telecel Faso network in the city of Ouagadougou (Burkina Faso in West Africa) are considered. Table 1 summarizes the technical details of these four links, namely their lengths, frequencies, and polarization. The transmitting and receiving power levels and therefore the attenuation of each link, are recorded at a one-minute sampling period.

As the rain events ground truth, we used data from four rain gauges of the Agence Nationale de la Météorologie (ANAM) of Burkina Faso. These gauges are installed near the considered four Telecel Faso CMLs. The rain gauge data were recorded with a 5-min sampling period in 2017 and a 15-min sampling period in 2019. Figure 1 shows the map of Burkina Faso, with a zoom on the city of Ouagadougou, which is our experimentation site. This figure shows the locations of the four CMLs and the four rain gauges. The red dots are the locations of the different rain gauges. The blue dots are the locations of the different transmission/reception towers and the CML are the green lines.

For the evaluation of our wet period detection method, we consider 15 rainfall events for which the CML attenuation data and rain gauge data are available. These data were recorded between September 2017 and October 2019. The rainfall events have durations ranging from 30 to 240 min, with water amounts varying between 0.48 and 59.41 mm.

Table 2 gives details of each rain event.

#### Description of the Proposed Method for Detecting Wet Periods

Consider the signal propagating between a transmitting and a receiving antenna of a mobile phone network. Let's note by  $T_x(t)$  the transmitting signal power level and by  $R_x(t)$ the receiving one, where t denotes the time variable. Without an automatic gain controller,  $T_x(t)$  is typically constant, while  $R_x(t)$  varies according to the weather conditions over the link (ITU-R, Rec P.525-4, 2019a; ITU-R, Rec P.676-12, 2019b; ITU-R, Rec P.838-3, 2005). The attenuation of the signal propagating over the link, a(t), is:

$$a(t) = T_x(t) - R_x(t) \tag{1}$$

In dry periods, (*t*) varies slightly. The occurrence of a rain event over the link causes an abrupt increase of the level of (*t*), proportionally to the rain intensity. To detect wet periods, we start by splitting the signal (*t*) into successive and distinct frames of duration  $\tau$ . Let's denote by *T* the frame *i* and *a* (*t*) the part of the attenuation signal on this frame:

$$a_{i}(t) = w_{i}(t) \times a(t) \text{ and } w_{i}(t) = \begin{cases} 1 \text{ if } t \in [t_{i}; t_{i} + \tau] \\ 0 \text{ elsewere} \end{cases}$$
(2)

w (t) is a sliding rectangular window of length  $\tau$ , starting at the time. The duration  $\tau$  should be chosen according to the rainfall characteristics of each region. The attenuation signal energy on the frame i,  $E_i$ , is given by the formula (3) (Grami, 2016):

$$E_i = \int_t^{t_i + \tau} a_i \left(t\right)^2 dt \tag{3}$$

To determine if the current frame *i* corresponds to a wet period, The Energy Variation (EVA) method compares the energy of frame *i*, with the energy of frame i - 1, while keeping in mind the status of frame i - 1.

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Fig. 1: Map of the four CMLs and four rain gauges used in the study

Table 1: Technical characteristics of the four CML links used in the s	study
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N	CML name	Link length (km)	Link frequency (GHz)	Antenna polarization
1	Kamboince-kaonghin	5.68	13.031	Vertical
2	Tampouy-rimketta	2.50	12.933	Vertical
3	Nagrin-gargin	3.15	12.821	Vertical
4	Universite-nabiyaar	1.45	13.143	Vertical

 Table 2: Rainfall detection results of the EVA and MSD methods √: Rain event detected, ×: Rain event not detected

							EVA	MSD
	Rain	Rain event	Rain event	Rain event	Rain event	Rain amount	detection	detection
CMLs	gauge	date	start time	end time	duration (min)	(mm)	results	results
Kamboince-kaonghin	P_kamboinse	20.09.2017	20:05	20:55	45	59,41.0		
		21.09.2017	03:00	0400	60	0,48.0	×	×
		31.07.2019	17:45	18:45	30	1,2.0	$\checkmark$	$\checkmark$
		31.07.2019	21:45	23:00	75	14,2.0	$\checkmark$	$\checkmark$
		31.07.2019-	23:45	00:15	30	0,8.0	×	×
		01.08.2019						
		01.08.2019	10:45	11:30	30	1,8.0	$\checkmark$	$\checkmark$
Tampouy-rimketta	P_tampouy	20.09.2017	20:15	20:55	40	8.0	$\checkmark$	$\checkmark$
Nagrin-gargin	P_tengandgo	20.09.2017	19:50	20:10	30	10,35.0	$\checkmark$	$\checkmark$
		31.07.2019	17:00	1800	60	34.0	$\checkmark$	$\checkmark$
		31.07.2019	21:30	2230	60	20,5.0	$\checkmark$	$\checkmark$
		01.08.2019	10:45	12:30	45	0,7.0	$\checkmark$	×
Universite-nabiyaar	P_aeroport	06.09.2019	20:05	20:55	50	10,2.0	$\checkmark$	$\checkmark$
•	•	30.09.2019	17:00	17:30	30	12,1.0	$\checkmark$	$\checkmark$
		02.10.2019	04:00	08:00	240	5.6	$\checkmark$	$\checkmark$
		10.10.2019	16:00	17:00	30	6.2	$\checkmark$	$\checkmark$

Let's define this energy variation by:

$$\delta_i = \frac{E_i - E_{i-1}}{E_{i-1}} = \frac{E_i}{E_{i-1}} - 1 \tag{4}$$

So, when two dry periods are consecutive, the level of the attenuation signal varies slightly across these two-time slots and thus  $\delta$  is relatively low. If a wet period follows a dry one, the attenuation increases with the onset of the rain event, and  $\delta$  become relatively high.

If a dry period follows a wet period, the attenuation decreases with the end of the rain and  $\delta$  takes again a relatively high value. Finally, if two wet frames are consecutive, the attenuation remains high over these two periods and therefore  $\delta$  are relatively low. The proposed decision rule for classifying frame  $T_{i-1}$  is as follows:

$$T_{i} \text{ is a wet period if } \begin{cases} \delta_{i} \geq \sigma \text{ and } T_{i-1} \text{ is dry} \\ -\sigma < \delta_{i} < \sigma \text{ and } T_{i-1} \text{ is wet} \end{cases}$$
$$T_{i} \text{ is a dry period if } \begin{cases} -\sigma < \delta_{i} < \sigma \text{ and } T_{i-1} \text{ is dry} \\ \delta_{i} < -\sigma \text{ and } T_{i-1} \text{ is wet} \end{cases}$$

 $\sigma$  is a threshold that quantifies the variation of the attenuation signal energy between two consecutive frames. This threshold can be easily adjusted according to the rainfall characteristics of each region, namely, rain mean duration and intensity.

#### **Results and Discussion**

The EVA method was evaluated on actual data recorded from the Telecel Faso network and compared with MSD, the most popular and used method in the literature for wet/dry classification. As mentioned in the data description section, 15 rainfall events, recorded between September 2017 and October 2019, were selected for the evaluation.

To apply EVA and MSD methods, we set the frame duration to 60 min, corresponding to the average duration of the 15 rain events considered. For the EVA method, we set the detection threshold to  $\sigma = 0.05$ , corresponding to a variation of 5% of the attenuation signal energy between two consecutive frames. For MSD the threshold is set to 0.5, as recommended by its authors.

Figure 2 shows the attenuation signals, rain gauge data, and wet periods detection results by EVA and MSD, for the rain events from July 31 to August 1, 2019, for the kamboince-kaonghin link. There were 6 wet time slots and one can see in Fig. 2 that all the wet periods were detected by both two methods.

For all the 15 rainfall events, there are a total of 26 wet periods and 232 dry ones. Table 3 presents the confusion matrix, while Table 4 and 5 give the confusion matrices of EVA and MSD respectively.

As for performance criteria, we use three indices derived from the confusion matrix namely: The True Positive Rate (TPR) given by formula (5), the Error Rate (ER) given by formula (6), and The Matthews Correlation Coefficient (MCC) given by formula (7). The Matthews Correlation Coefficient (MCC) summarizes the four values of the confusion matrix into a single measure and is commonly used as a binary classification measure in machine learning. This measure accounts for the asymmetric ratio between wet and dry events. It is only high if the classifier performs well in both classes:

$$TPR = \frac{TP}{TP + FN}$$
(5)

$$ER = \frac{FP + FN}{TP + FN + FP + TN}$$
(6)

$$MCC = \frac{TP \times TN - FP + TN}{\sqrt{(TP + FP)(TP + FN)(TN + FP)(TN + FN)}}$$
(7)

In formulas (5), (6), and (7), TP is the number of true positives, FP is the number of false positives, TN is the number of true negatives and FN is the number of false negatives, as shown in Table 3.

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		Rain gauge		
		Wet	Dry	
CMLs	Wet	True wet (TP)	False wet (FP)	
	Dry	False dry (FN)	True dry (TN)	

 Rain gauge

 Wet
 Dry

 CMLs
 Wet
 22
 0

 Dry
 4
 232

		Rain gauge		
		Wet	Dry	
CMLs	Wet	21	2	
	Dry	5	230	

Table 6: Performance of the EVA and MSD methods

	TPR %	ER %	MCC %
EVA	84.61	1.56	91.20
MSD	80.76	2.73	84.41



Fig. 2: CML Attenuation, rain gauge data, and wet periods detection results, from July 31 to August 1, 2019, for the KAMBOINCE-KAONGHIN link

One can see from Tables 4, 5, and 6 that the EVA method presents better results than MSD. The true positive rate of EVA is 84.61%, which is quite comparable to the performance of other methods described in the literature. Moreover, EVA's Matthews Correlation Coefficient (MCC) is higher than 0.9, which demonstrates that it can discriminate between wet and dry periods with high accuracy. We can also see from Table 2 that, for the 3 rain events for which the rain amount is less than 1 mm, EVA detected 1, while MSD does not. This confirms that the proposed new method is more sensitive.

#### Conclusion

In this study, we proposed a new method for detecting wet periods from the attenuation signal of commercial microwave telecommunications links.

The proposed method, named EVA, takes into account the variation of the energy variation between two consecutive frames, as well as the state of the previous frame to determine the state of the current frame. Based on actual data from the mobile phone operator Telecel Faso, EVA detects 84.61% of rain events and has an error rate of 1.56%. The parameters of EVA, namely the duration of the frames and the threshold of energy variation to be considered for detecting rainfall events, can be adjusted according to the rainfall characteristics of each region.

Future work will focus on the estimation of the rain amount from attenuation signals of commercial microwave links to derive rain maps. Short-time prediction of rainfall will also be investigated.

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# **Author's Contributions**

Wend Yam Serge Boris Ouedraogo: Original draft, source codes, data interpretation, manuscript writing, and validation. Give final approval of the version to be submitted and any revised version.

**Moumouni Djibo:** Original draft, part of the source codes, data interpretation, manuscript writing, and validation. Give final approval of the version to be submitted and any revised version.

**Ali Doumounia:** Part of the data and give final approval of the version to be submitted and any revised version.

Serge Roland Sanou, Moumouni Sawadogo and Idrissa Guira: Give final approval of the version to be submitted and any revised version.

**François Zougmoré:** Supervised the work and gives final approval of the version to be submitted and any revised version.

# Ethics

This article is original and contains unpublished material. It is confirmed that all of the authors have read and approved the manuscript and there are no ethical issues involved.

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