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ADALM-Pluto SDR as a Tool for S-parameter Estimation: A Comparative Study of Various System Identification Procedures

Filip Nešković
School of Electrical Engineering
University of Belgrade
Belgrade, Serbia
fneskovic@etf.rs

Nikola Basta
School of Electrical Engineering
University of Belgrade
Belgrade, Serbia
nbasta@etf.rs

Milka Potrebić Ivaniš
School of Electrical Engineering
University of Belgrade
Belgrade, Serbia
milka_potrebic@etf.rs

***Abstract*—In this work we propose an affordable measurement setup for scalar network analysis using ADALM-Pluto software defined radio and a number of system identification procedures used for the purpose of estimating magnitude of *S*-parameters. The proposed algorithms are employed for the purpose of estimation of the S-parameters of passive microwave circuits. A comparison of these procedures is given considering measurement of magnitudes of transmission and reflection coefficients with respect to frequency.**

***Keywords*—System Identification, Signal Processing, ADALM-Pluto SDR, Calibration, Microwave circuits, Scattering parameters, MATLAB**

I. Introduction

Microwave measurements are an important field of microwave-engineering education. In industry, prototype measurement and verification is a critical step before final production. Linear passive microwave circuits are usually characterized by means of their scattering parameters using either scalar network analyzers (SNA) or vector network analyzers (VNA). Scalar network analyzers are relatively simple, and they are primarily used for measuring magnitude of S-parameters [1]. On the other hand, vector network analyzers can measure both phase and magnitude, however they are more complex and therefore, significantly more expensive.So far, researchers and engineers have discovered many applications of microwave measurements, such as: using scalar network analysis for possible wood defect detection [2]; scalar network analysis applied to biomedical dehydration monitoring [3]; measuring various capacitor parameters using vector network analysis [4] etc.

Given that these devices are hard to obtain for a considerate number of individuals and institutions, a simple and cost-effective solution for scalar network analysis is proposed. With the proposed solution simple microwave circuits can be analyzed in range of 70 MHz – 6 GHz, which is more than enough for educational purposes.

The rest of the paper is organized as follows. Hardware setup is explained in Section II. Calibration, as well as formulas for obtaining S-parameters, are explained in Section III. Section IV explains various identification algorithms that were tested for performance. Measurement results and their interpretations are given in Section V. Conclusion is given in Section VI.

II. Hardware Setup

The basic hardware setup for estimation of S_{21}-parameter, i.e., transmission coefficient, consists of a software defined radio (SDR), produced by Analog Devices, ADALM-Pluto [5], two SMA RG316 cables, a set of affordable SMA standards – SHORT, THRU and LOAD, a 10 dB attenuator (ATT), and a PC for control, acquisition and display of results. Additionally, a directional coupler of 20-dB coupling level is used for measurement of S_{11}-parameter, i.e., the reflection coefficient. The setups are shown in Figs. 1 and 2.

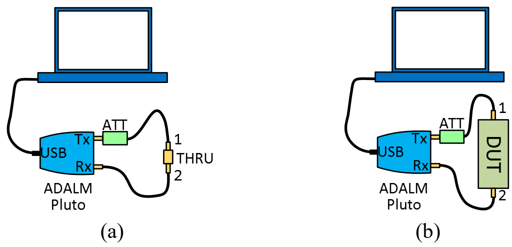

Fig. 1. Hardware setup for measurement of S_{21}- parameter. DUT stands for device-under-test. (a) THRU Calibration. (b) Measurement of DUT.

ADALM-Pluto is a single-input-single-output (SISO) SDR module with nominal operating frequency band of 325 MHz – 3.8 GHz, but can be extended to 70 MHz – 6 GHz [5]. The transceiver uses 12-bit A/D and D/A converters and up to 56 MHZ of RF bandwidth. Although ADALM-Pluto was considered in the past as a low-cost alternative to VNA [6], the presented analysis will show performance of non-canonical excitation as well as their accuracy within the extended range.

In our setup, the test flow is as following: the baseband excitation signals are defined in MATLAB [7] scripts and are sent to ADALM-Pluto through a USB connection. The signal is upconverted (modulated) to the carrier frequency f_c within the SDR and sent through its transmitter (Tx) to the input port of device-under-test (DUT). The output RF signal is received by the SDR receiver (Rx), where RF filtering, down-conversion, downsampling, and baseband filtering take place.

Finally, samples of complex baseband received signal are sent through USB back to PC and saved as a MATLAB

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variable. This procedure is repeated for a set of observed RF frequencies, f_c.

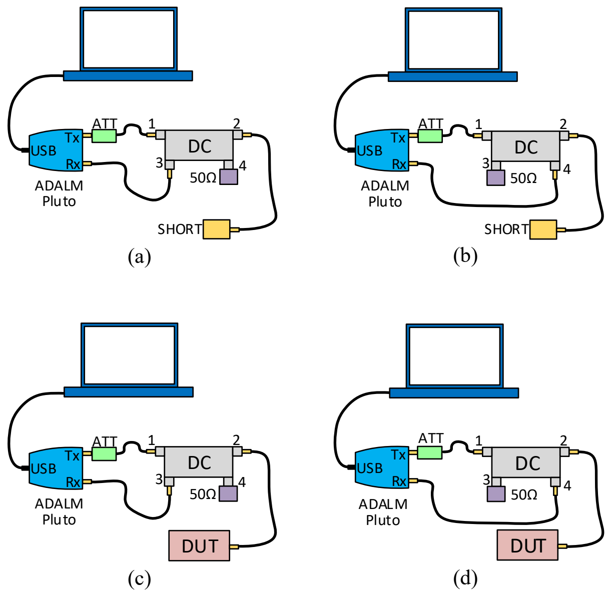

Fig. 2. Hardware setup for measurement and calibration of S_{11}- parameter. DC stands for directional coupler. (a) SI_{CAL}. (b) SR_{CAL}. (c) SI_{DUT}. (d) SR_{DUT}.

III. Calibration

Essential part of estimating an S-parameter is taking effects produced by the measurement equipment into consideration – a process which is also known as calibration. This includes impact of cables, connectors, attenuator, coupler and ADALM-Pluto SDR, itself.

In case of estimating S_{21}, calibration measurement is taken with a THRU component, the effect of which is considered negligible, compared to the rest of the measurement configuration (Fig. 1a). This way we obtain SI_{CAL}, that is an S_{21} estimation of the measurement equipment. Now, substituting THRU with DUT, as shown in Fig. 1b, we obtain S_{21} estimation of the measurement equipment together with the DUT. Using (1), we extract S_{21} of the DUT alone.

$$S_{21} = \frac{S_{21DUT}}{S_{21CAL}} . \tag{1}$$

In the case of estimation of the S_{11}-parameter, two calibration measurements (SI_{CAL} , SR_{CAL}) are performed as shown in Figs. 2a and 2b, where incident and reflected power is recorded in the presence of SHORT element in the direct path of the directional coupler (DC). By placing DUT instead of SHORT, additional two measurements are performed, as shown in Figs. 2c and 2d, namely incident and reflected power in the presence of a single port DUT (SI_{DUT} , SR_{DUT}). Estimation of the reflection coefficient is obtained using (2).

$$S_{11} = \frac{\dfrac{SR_{DUT}}{SI_{DUT}}}{\dfrac{SR_{CAL}}{SI_{CAL}}} . \tag{2}$$

IV. Algorithms

System identification is a subfield of control systems theory, used for estimation of unknown parameters that describe systems (being linear or nonlinear, time invariant or time variant) in either frequency or time domain. Recent developments in the field include, but are not limited to: fault detection and isolation [8]; in-process machine tool dynamics estimation [9] etc.

Given that microwave filters and antennas represent linear time-invariant (LTI) systems with respect to their scattering parameters, many widely known system identification algorithms are candidates for application in estimation of S-parameters. In this work, a selection of these algorithms [10, 11] was made in order to perform a comparative analysis: (i) sinusoidal testing, (ii) multisine testing, (iii) random noise excitation using white Gaussian noise (WGN), and (iv) empirical transfer function estimation, employing also WGN as the input function.

A. Sinusoidal Testing

Sinusoidal testing [10] considers an input signal in form:

$$u(t) = A\sin(2\pi f t + \alpha) , \tag{3}$$

where amplitude of the signal is given by A, frequency of the signal is given by f and phase offset of the signal is given by α. For identifying an LTI system, output signal model of the system will be given by

$$y(t) = B\sin(2\pi f t + \beta) , \tag{4}$$

where B is output amplitude and β is output phase offset.

B. Multisine Testing

Unlike basic sinusoidal testing approach, multisine testing [11] considers a series of sine components

$$u(t) = \sum_{m=1}^{M} A_m \sin(2\pi f_m t + \alpha_m) , \tag{5}$$

where A_m , f_m and α_m are amplitudes, frequencies and phase offsets of the input baseband signal, respectively. The output signal is, therefore expected to be in similar form

$$y(t) = \sum_{m=1}^{M} B_m \sin(2\pi f_m t + \beta_m) , \tag{6}$$

where the corresponding amplitudes, frequencies and phase offsets are given by B_m , f_m and β_m respectively.

C. Random Noise Excitation

In random-noise-excitation testing [11] output signal is obtained while feeding the system with WGN [12], i.e. an input function $u(t)$ such that:

$$R_{uu}(t_1, t_2) = \sigma^2 \delta(t_1 - t_2) , \tag{7}$$

where $R_{uu}(\tau)$ is the autocorrelation function of WGN signal $u(t)$, $\delta(t)$ is Dirac delta function and σ^2 is the signal variance.

D. Empirical Transfer Function Estimation - ETFe

In ETFe approach [10], the output signal is obtained using also a WGN as input, as given in (7). Since the transmitted and received signals are digitized, they can be represented by time-domain sequences $u[n]$ and $y[n]$. In this method, the respective discrete Fourier transformations (DFTs) of input and output, $U[k]$ and $Y[k]$, are computed for a predefined set of L frequencies, where $k = 0,1,2,..., L$. Finally, ETFe is obtained by:

$$G[k] = \frac{Y[k]}{U[k]}. \quad (8)$$

E. Measurement Data Model

As noted before, SDR platform provides a response in the form of a complex discrete time-domain sequence $y[n]$, but our analysis relies on its DFT, $Y[k]$. In sinusoidal, multisine and random-noise-excitation procedures, estimation is computed as a sum

$$S(f_c) = \sqrt{\sum_{k=0}^{N-1} |Y[k]|^2}. \quad (9)$$

which is square root of narrow-band-power around central frequency f_c.

Particularly, for the ETFe procedure, a median estimator is applied to vector $\tilde{G}[k] = \tilde{Y}[k]/\tilde{U}[k]$, where $\tilde{Y}[k]$ and $\tilde{U}[k]$ are DFTs of sequences of moduli, $|y[n]|$ and $|u[n]|$, respectfully. This estimator is applied both to calibration and DUT measurements, following (1) and (2).

V. Measurement Results

A set of parameters for each of the testing algorithms was defined with respect to formulations in Section IV and is given in Table I. In all tests the baseband sampling frequency was $f_s = 100\,\text{kHz}$ and downsampling factor was 4.

TABLE I. ALGORITHM PARAMETERS

Algorithm	Parameters
Sinusoidal testing	$f = 1\,\text{kHz}$ $\alpha = -\pi/2$
Multisine testing	$f_m \in \{5,10,15,20,25\}\,\text{kHz}$
Random noise excitation	$\sigma^2 = 0.5$ 250 samples of WGN 'linear' power level
Empirical transfer function estimation	$\sigma^2 = 0.5$ 250 samples of WGN 'linear' power level

An assortment of passive microwave devices considered in this work is presented in Fig. 3. Transmission coefficient, S_{21}, was measured for an LC bandpass filter, a shielded hairpin bandpass filter and a commercial lowpass filter. Reflection coefficient, S_{11}, of a patch antenna was measured using a directional coupler.

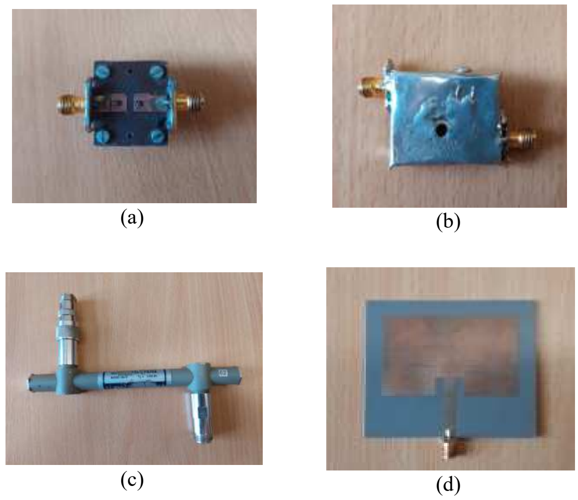

Fig. 3. Devices-under-test. (a) LC bandpass filter. (b) Hairpin bandpass filter. (c) Commercial lowpass filter. (d) Patch antenna.

In Figs. 4 – 7 estimated magnitudes of S-parameters of components from Fig. 3 are shown. Measurement results are summarized in Tables II – V.

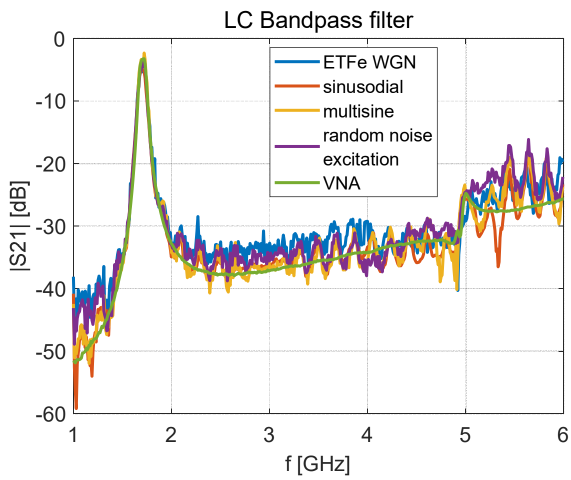

Fig. 4. Magnitude of S21 parameter of LC bandpass filter from Fig. 3a. .

It is evident that all of the proposed algorithms are able to estimate resonant frequencies relatively accurately, with acceptable error levels compared to measurements obtained by using a professional VNA.

From Tables II and III, it can be concluded that estimation using random noise excitation method gives overall very close estimation of magnitudes of resonant frequencies, in comparison to other considered methods.

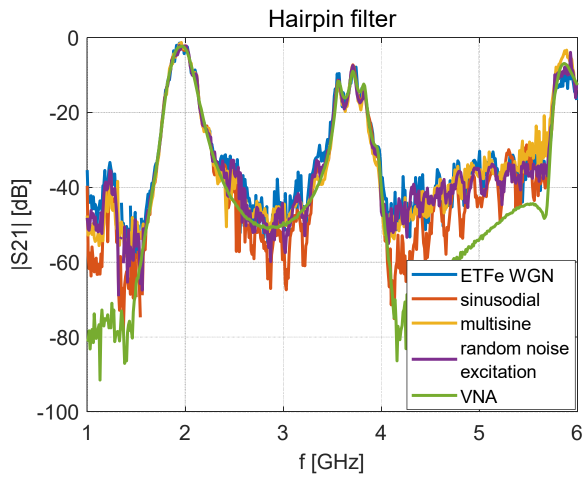

Fig. 5. Magnitude of S_{21} parameter of hairpin bandpass filter from Fig. 3b.

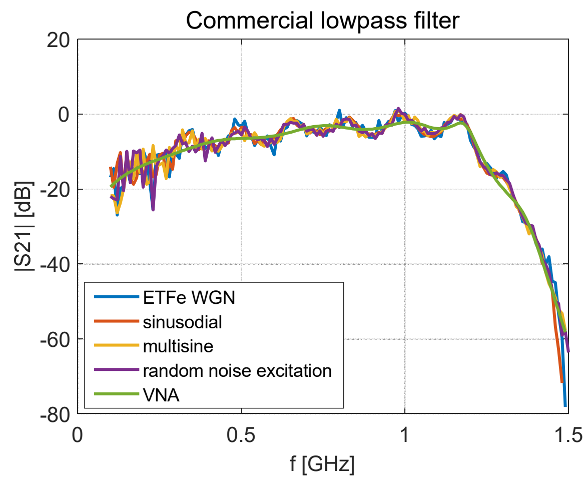

Fig. 6. Magnitude of S_{21} parameter of lowpass filter from Fig. 3c.

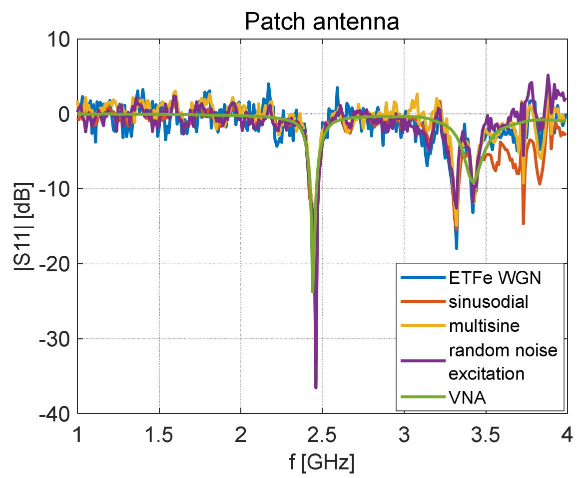

Fig. 7. Magnitude of S_{11} of patch antenna from Fig. 3d.

From Table IV, we see that all of the other proposed algorithms have a relatively low RMSE values. Moreover, all of these algorithms exhibit a reduction in RMSE values by increasing the observed frequency interval.

In Table V, it is implied that estimation using multisine testing method performs better magnitude estimation than all of the other methods. Also, it shows that ETFe estimation gives better resonant frequency estimation.

TABLE II. S_{21} – LC BANDPASS FILTER

Method	**Maximum [dB]**	**Maximum frequency [GHz]**
VNA	-3.22	1.71
Sine estimation	-4.35	1.70
Multisine estimation	-2.33	1.72
Random noise excitation	-3.42	1.71
Empirical transfer function estimation	-2.99	1.72

TABLE III. S_{21} – HAIRPIN BANDPASS FILTER

Method	**Maximum [dB]**	**Maximum frequency [GHz]**
VNA	-2.3	1.97
Sine estimation	-2.21	1.95
Multisine Estimation	-1.29	1.96
Random noise excitation	-2.11	1.94
Empirical transfer function estimation	-1.43	1.94

In Figs. 4 – 7, we observe that sinusodial testing method is prone to greater variations in values, especially at lower magnitudes (–40 dB and lesser), giving false conclusion about the dynamics of magnitude and effects of possible reflections. This phenomenon is not exhibited by other algorithms, which have steadier dynamics and give much better interpretations of a component's dynamics in the corresponding range of frequencies (Fig. 5). Among other algorithms, however, multisine testing method exhibits steadier local dynamics behavior in comparison to the other two algorithms. Also, in comparison to ETFe and random noise excitation, the multisine method exhibits lesser bias in estimating magnitude characteristics at lower magnitude levels (Fig. 4).

TABLE IV. S_{21} – LOWPASS FILTER

Method	RMSE (dB) up to 400MHz	RMSE (dB) up to 800MHz	RMSE (dB) up to 1.2GHz
Sine estimation	3.40	2.59	2.29
Multisine estimation	3.51	2.67	2.36
Random noise excitation	3.95	2.87	2.49
Empirical transfer function estimation	3.92	3.13	2.72

TABLE V. S_{11} – PATCH ANTENNA

Method	Maximum [dB]	Maximum frequency [GHz]
VNA	-23.78	2.44
Sine estimation	-35.73	2.46
Multisine Estimation	-25.42	2.46
Random noise excitation	-36.57	2.46
Empirical transfer function estimation	-15.13	2.45

VI. CONCLUSION

In this paper, it was shown that ADALM-Pluto SDR has the potential to serve as a simple and cheap, yet effective and to-a-certain-degree accurate scalar network analyzer for purposes of education and preliminary measurements. It was also shown that the chosen set of identification algorithms provides useful insights into performance of a microwave component, considering the transfer functions that correspond to its frequency-domain scattering parameters.

In future work, additional identification algorithms will be investigated in order to determine compatibility with different classes of microwave components, and which of them could give more information about certain properties of these classes of components. Moreover, in further research, other measurement and calibration configurations will be considered in order to achieve more accurate measurements and additional insight into a specific set of properties of a class of microwave components. Additionally, it would be beneficial to investigate if ADALM-Pluto SDR can serve as a full vector network analyzer.

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REFERENCES

[1] D. M. Pozar, *Microwave Engineering*, 4th ed. Hoboken, New Jearsey, USA: John Wiley & Sons, 2011.

[2] M. Radwan, N. Becker, D. V. Thiel, H. G. Espinosa, "In-Line Wood Defect Detection Using Simple Scalar Network Analysis," *Sensors-Basel*, vol. 22, no. 23, pp. (9495) 1-9, Dec. 2022.

[3] M. Hoffman, J. Nehring, R. Weigel, G. Fischer, D. Kissinger, "A Wideband Scalar Network Analyzer for Biomedical Dehydration Measurements," Proc. 35th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC), Osaka, Japan, pp. 4050-4053, 3-7 July, 2013.

[4] D. Steppins, G. Asmanis, A. Asmanis, "Measuring Capacitor Parameters Using Vector Network Analyzers", *Electronics*, vol. 18, no. 1, pp. 29-38, June, 2014.

[5] ADALM-PLUTO Overview, [Online]. Available: https://wiki.analog.com/university/tools/Pluto

[6] A. Raza, A. Jabbar, D. A. Sehrai, H. Atiq, R. Ramzan, "SDR Based VNA for Characterization of RF Sensors and Circuits," Proc. 2021 1st International Conference on Microwave, Antennas & Circuits (ICMAC), Islamabad, Pakistan, pp. 1-4, 21-22 December, 2021.

[7] The MathWorks Inc. (2022). MATLAB version: 9.12.0 (R2022a), Natick, Massachusetts: The MathWorks Inc. [Online]. Available: https://www.mathworks.com/

[8] A. Marjanovic, G. Kvascev, Ž. Djurovic, "Comparison of Identification procedures in the Frame of Fault and Detection and Isolation", Proc. 2012 IEEE International Conference on Control Applications (CCA), Dubrovnik, Croatia, pp. 1697-1702, 3-5 Oct. 2012.

[9] V. O. A. Akbari, Y. Mohammadi, M. Kuffa, K. Wegener, "Identification of in-process machine tool dynamics using forced vibrations in milling process", *Int. J. Mech. Sci.*, vol. 239, pp. (107887) 1-11, Feb., 2023.

[10] K. J. Keesman, *System Identification*, Berlin, Germany: Springer, 2011.

[11] J. Shoukens; R. Pintelon, E. van den Ouderaa, J. Renneboog, "Survey of Excitation Signals for FFT Based Signal Analyzers"; *IEEE T. Instrum. Meas.*, vol. 37, no. 3, Sept. 1988.

[12] A. L. Garcia, *Probability, Statistics and Random Processes for Electrical Engineering* , 3rd ed. Upper Saddle River, NJ, USA: Pearson Prentice Hall, 2008.