Power Measurement in DVB-T Systems: on the Suitability of Parametrical Spectral Estimation in DSP-Based Meters

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Abstract—Performance assessment and large scale monitoring of DVB-T transmission apparatuses is nowadays a pressing need due to the rapid growth of the related broadcasting network in many countries. Power measurement, in particular, plays a very important role since RF and IF signal power, RF channel power, RF and IF power spectrum, noise (or unwanted) power, and power efficiency are relevant parameters to be measured as accurately as possible. Although modern spectrum analyzers and high-performance vector signal analyzers exhibit satisfying accuracy and repeatability, their cost, weight and size make them unsuited to the purpose. Current research activity of the authors is focused on the design and realization of a DSP-based meter for power measurement in DVB-T systems, capable of granting good accuracy, satisfying repeatability, reduced measurement time and cost effectiveness. The paper deals with the digital signal processing algorithm to be implemented in the meter, paying attention to parametric PSD estimators for their reduced memory requirement and potentially limited computational burden.

In particular, all algorithm capable of granting good metrological performance and fast measurement rate is implemented and made operative. Simulation and emulation stages are properly designed in order to regulate the most relevant parameters of the adopted PSD estimators according to the specific features of the signals involved. A number of experiments on actual DVB-T signals are conducted, the results of which are compared to those provided by competitive measurement solutions.

Index Terms—DVB-T, Channel power measurement, Nonparametric spectral estimation, Parametric spectral estimation, Power measurement, PSA, RF measurements, RSA, Spectrum analyzer, VSA, WOSA estimation.

I. INTRODUCTION

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igital video broadcasting (DVB) represents a considerable technological opportunity to make innovation in standard television; whether via satellite (DVB-S), via cable (DVB-C), or terrestrial (DVB-T), it is revolutionizing television transmissions [1]. With special regard to DVB-T, the complex modulation technique adopted (Coded Orthogonal Frequency Division Multiplexing, COFDM) poses a completely new measurement challenge for radiofrequency (RF) signal integrity and physical layer analysis. A new set of measurements for monitoring and assessing the performance of DVB-T systems and apparatuses is, in fact, required (see Table. I). Power measurements, in particular, play a very important role. Radiofrequency (RF) and intermediate frequency (IF) signal power, RF channel power, RF and IF power spectrum, noise (or unwanted) power, and power efficiency are relevant parameters to be measured as accurately as possible [2]. RF power meters equipped with proper probes and spectrum analyzers can be used to the purpose [2]. The former are specifically mandated to peak and/or average power measurement, while the use of the latter is mandatory whenever the integration of the input signal power spectrum over a certain frequency range (for example, channel power measurement) is involved [3].

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TABLE I

DVB-T measurement parameters and their applicability according to the ETSI TR 101290 (T=TRANSMITTER, N=NETWORK, R=RECEIVER)}

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Traditional spectrum analyzers, however, suffer from low accuracy and repeatability problems, the entity of which depends on the specific measurement. This is true in the presence of any signal characterized by high PAR (peak to average power ratio), like OFDM signals. Peak power can be much greater than average one, thus making the signal exhibit rapid changes in time domain (noise like nature) that can disturb the proper operation of these instruments [4],[5]. The cited problems have been mitigated both by modern spectrum analyzers (Express Spectrum Analyzer, ESA, Performance Spectrum Analyzer, PSA, Real Time Spectrum Analyzer, RSA) and high-performance vector signal analyzers (VSA).

The authors already showed in [6],[7] that good reliability and repeatability in power measurement in DVB-T systems can be assured through the combined use of a proper digital signal processing algorithm and minimum hardware. A new method, based on nonparametric power spectral density (PSD) estimation, was in particular proposed (Fig. 1). Only a common downconversion stage, from RF to IF, and a general purpose data acquisition system (DAS) are required. After digitizing the input RF signal, the method first gains its true power spectrum through the use of a weighted overlapped segment averaging (WOSA) estimator, and then evaluates the quantities of interest by applying very straightforward measurement algorithms to the attained PSD. The method was tested in simulation and emulation environments, as well as applied to a number of actual signals. The obtained results highlighted satisfying performance if compared to that exhibited by competitive and expensive measurement solutions, like modern spectrum analyzers and high-performance vector signal analyzers.

Current activity is focused on the design and realization of a DSP-based meter for power measurement in DVB-T systems, mainly devoted to performance assessment and large scale monitoring. Satisfying repeatability, reduced measurement time (fast measurement rate) and cost effectiveness are, in particular, pursued. To this aim, a suitable downconversion circuitry has already been arranged, and a proper digitizing section is going to be selected. Concerning the digital signal processing algorithm, even though that proposed in [6],[7] assures remarkable repeatability, its implementation in cost-effective DSP-based architectures could be very troublesome.

More specifically, the WOSA estimator requires a great number of fast Fourier transforms (FFTs) to be calculated. To attain an adequate frequency resolution, each FFT has to involve a non-trivial number of acquired samples, to be preserved in the local memory of the meter. A relevant storage capability, often incompatible with typical DSP-based architectures and unsuited to the desired research target, is thus claimed. Moreover, any attempt to reduce the record length could severely compromise the achievable repeatability [6],[7]. To overcome the cited drawback, a rough version of an alternative algorithm, in the following referred as new algorithm, for power measurement in DVB-T systems, capable of meeting the reduced memory resources of a cost-effective DSP-based meter and granting the same promising performance of the old algorithm, peculiar to the method in [6],[7], has been proposed in [8]. The attention has mainly been paid to the PSD estimation section of the old method, and in particular to the opportunity of replacing WOSA estimator with a parametric approach. Several reasons have justified the choice:

(i) parametric spectral estimation can exhibit a reduced convergence time;
(ii) parametric spectral estimation is entitled to provide more significant results than those achievable from nonparametric approaches when the acquired record covers a relatively short time interval;
(iii) WOSA estimator-based measurement algorithm yields PSD estimates from windowed set of data. The unavailable data values outside the window are implicitly zero, normally an unrealistic assumption that can lead to distortions in the spectral estimate. Sometimes it’s possible to have some knowledge about the process from which the data samples are taken. This information may be used to construct a model and regulate its parameters in such a way as to best approximate the process that generated the observed time sequence [9];
(iv) parametric spectral estimation can be implemented in an optimized manner (sequential estimation), thus allowing measurement results to be updated whenever a new sample is available, and removing the need of locally storing a large number of acquired samples [9].

The paper aims at deeply extending the interesting results achieved in [8]. In particular, (i) optimized versions of the new measurement algorithm are implemented and made operative; (ii) simulation and emulation stages are properly designed in order to regulate the most relevant parameters of the adopted PSD estimators according to the specific features of the signals involved; (iii) a number of experiments on actual DVB-T signals are conducted; (iv) the results obtained both in the emulation stage and on actual signals are compared to those provided by competitive measurement solutions, such
as high performance power meters, traditional spectrum analyzers, high performance spectrum analyzers, and real time spectrum analyzers.

II. THEORETICAL BACKGROUND

In this section some theoretical notes on parametric spectral estimation are given; further details can be found in [9]-[12].

Parametric estimation methods suppose that the analyzed signal is the output of a model, represented as a linear system, driven by a noise sequence \( \varepsilon_n \). They evaluate the PSD of the signal by estimating the parameters (coefficients) of the linear system that hypothetically "generates" the signal. Among the various methods, autoregressive (AR) approaches are widespread. Computational burden related to AR approaches is, in fact, significantly less than those required to implement moving average (MA) or autoregressive-moving average (ARMA) parameter estimation algorithms [9].

A stationary autoregressive process of order \( p \), AR\((p)\), satisfies the equation:

\[
x_k = \sum_{n=1}^{p} a_{p,n} x_{k-n} + \varepsilon_k
\]

where \( a_{p,1}, a_{p,2}, \ldots, a_{p,p} \) are fixed coefficients and \( \{\varepsilon_n\} \) is a white noise process with variance \( \sigma^2 \). The PSD of the stationary process described by AR\((p)\) is totally described by the model parameters and the variance of the white noise process. It is given by:

\[
S(f) = \frac{\sigma^2 T_s}{1 + \sum_{n=1}^{p} a_{p,n} e^{-j2\pi nf}} \quad \text{if } f \leq f_n
\]

where \( T_s = 1/f_s \) is the sampling interval and \( f_s = 1/(2T_3) \) is the Nyquist frequency.

Consequently, known \( p \), it is necessary to properly estimate the \( p+1 \) parameters \( a_{p,1}, a_{p,2}, \ldots, a_{p,p} \) and \( \sigma^2 \). To reach this goal, the relationship between the AR parameters and the autocorrelation sequence (known or estimated) of \( x_n \) has to be fixed as described below.

A. Yule-Walker Equations

If both sides of (1) are multiplied by \( x_{n-k}^* \), the following expression is obtained

\[
x_{n-k} x_{n-k}^* = \sum_{n=1}^{p} a_{p,n} x_{n-k} x_{n-k}^* + \varepsilon_k x_{n-k}^* .
\]

Making the expectations, the autocorrelation sequence is evaluated:

\[
R_{xx}(k) = E[x_{n-k} x_{n-k}^*] = \sum_{n=1}^{p} a_{p,n} R_{xx}(k-m) + E[\varepsilon_k x_{n-k}^*] .
\]

The plausible fact that \( E[\varepsilon_k x_{n-k}^*] = 0 \), for \( k > 0 \), implies that

\[
E[\varepsilon_k x_{n-k}^*] = E[\varepsilon_k] + \sum_{n=1}^{p} a_{p,n} E[x_{n-k} x_{n-k}^*] = \sigma_k^2 .
\]

Hence, the evaluation of the equation (4) for \( k = 0,1, \ldots, p \) makes it possible to obtain the so-called augmented Yule-Walker equations

\[
R_p A_p = \Sigma_p
\]

where \( A_p = [a_{p,1}, \ldots, a_{p,p}]^T \), \( \Sigma_p = [\sigma_{p,0}, \ldots, 0]^T \) and

\[
R_p = \begin{bmatrix}
R_{xx}(0) & R_{xx}(-1) & \cdots & R_{xx}(-p) \\
R_{xx}(1) & R_{xx}(0) & \cdots & R_{xx}(-p+1) \\
\vdots & \vdots & \ddots & \vdots \\
R_{xx}(p) & R_{xx}(p-1) & \cdots & R_{xx}(0)
\end{bmatrix}
\]

is the Toeplitz autocorrelation matrix \((p+1)\times(p+1)\).

If we haven’t a stationary process \( \{x_n\} \), but we are in the presence of a time series that is a realization of a portion \( x_1, x_2, \ldots, x_N \) of any discrete-parameter stationary process, replacing \( R_{xx}(k) \) with

\[
\hat{R}_s(k) = \frac{1}{N} \sum_{n=0}^{N-k} x_{n+k} x_{n-k}^* \quad \text{for } k = 0, \ldots, p
\]

it’s possible to solve the system (6) by inversion.

B. Levinson-Durbin Algorithm

To avoid the matrix inversion, which is a time-consuming task and performed using the Gaussian elimination, that requires operations of order \( p^3 \), denoted \( o(p^3) \), the system (6) can be solved through Levinson-Durbin recursions [10],[11], which require only \( o(p^2) \) operations. The algorithm proceeds recursively computing the AR parameters for the order \( k \) from the ones previously determined for the order \( k-1 \).

In particular, the recursive algorithm is initialized by

\[
a_{i,1} = \frac{R_{xx}(1)}{R_{xx}(0)}
\]

\[
\sigma_i^2 = [1 - |a_{i,1}|^2] R_{xx}(0)
\]

and the recursion for \( k=2,3, \ldots , p \) is given by

\[
a_{i,k} = \frac{R_{xx}(k) + \sum_{l=1}^{k-1} a_{i,k-l} R_{xx}(k-m)}{\sigma_i^2}
\]

\[
a_{i,m} = a_{i,m+1} + a_{i,k} a_{i,k-m}^* , \quad 1 \leq m \leq k-1
\]

\[
\sigma_i^2 = \sigma_{i-1}^2 [1 - |a_{i,k}|^2]
\]

where \( a_{i,k} \) is called reflection coefficient [10].

It’s important to note that, even though Levinson-Durbin recursions grant a significant reduction of the computational burden, the need to estimate the autocorrelation sequence \( R_{xx}(k) \), in order to solve the system (6), still exists.

This algorithm is useful when the correct model order is not known a priori, since the expressions (8)-(12) can be used to generate successfully higher order models until the modeling error \( \sigma_i^2 \) is reduced to a desired value.

C. Forward Linear Prediction Algorithm

In literature it’s possible to find several least square estimation procedures that operate directly on the data to yield better AR parameter estimates. These techniques often produce better AR spectra than that obtained with the Yule-Walker approach.
Assume that the sequence \(x_0, \ldots, x_{N-1}\) is used to find the \(p\)th order AR parameter estimates. The forward linear predictor is [13]:

\[
\hat{x}_n = \sum_{k=1}^{p} a_{p,k} x_{n-k}.
\] (13)

It’s possible now to define the forward linear prediction error in this way:

\[
e_p(n) = x_n - \hat{x}_n = \sum_{k=1}^{p} a_{p,k} x_{n-k} \quad \text{for } p \leq n \leq N-1
\] (14)

where \(a_{p,0} = 1\), and to compute \(e_p(n)\) for \(n = p\) to \(n = N-1\)

\[
e_p(p) = x_p, \quad e_p(N-1) = x_{N-1} \quad \begin{bmatrix} x_p & \cdots & x_0 & \cdots & \vdots & \cdots & x_p \end{bmatrix}
\] (15)

with \(x_p\) a \((N-p)\times(p+1)\) Toeplitz matrix.

The approach followed to estimate \(a_{p,k}\) consists of minimizing a sum of \(e_p(n)\), called prediction error energy

\[
SS_p = \sum_{n=1}^{N-p} |e_p(n)|^2 = \sum_{n=0}^{N-p} a_{p,k} x_{n-k}^2 = E^H E.
\] (16)

Using an alternative description of the \(N-p\) error equations (15) such as

\[
E = \begin{bmatrix} y^T & \mathbf{X}^T \end{bmatrix}
\] (17)

where \(y = [x_{p-1}, \ldots, x_0]^T\), \(a = [a_{p,1}, \ldots, a_{p,p}]^T\) and

\[
\mathbf{X} = \begin{bmatrix} x_{p-1} & \cdots & x_0 \\
\vdots & \ddots & \vdots \\
x_{N-2} & \cdots & x_{N-p-1} 
\end{bmatrix}
\]

the prediction error energy (16) may be expressed as

\[
SS_p = E^H E = y^H y + y^H X a + a^H X^H y + a^H X^H X a.
\] (18)

Noting that (18) may be written as

\[
SS_p = y^H y - y^H X (X^H X)^{-1} X^H y + (X^H y + X^H X a) (X^H X)^{-1} (X^H y + X^H X a)
\]

only the last term on the right hand side of (19) is function of the unknown parameter \(a\), and due to its Hermitian symmetry, this term will always be real and positive. In order to minimize \(SS_p\), this term must be set to zero, obtaining

\[
X^H y + X^H X a = 0
\] (20)

where \(0_p\) is the all-zeros vector.

The minimum prediction error energy is obtained by substituting (20) into (18), yielding

\[
SS_{p,\min} = y^H y + y^H X a.
\] (21)

Equations (20) and (21) may be combined into a single set of \(p+1\) simultaneous equations as follows

\[
\begin{bmatrix} y^H y & y^H X \end{bmatrix} \begin{bmatrix} 1 \\ n \end{bmatrix} = \begin{bmatrix} y^H X \end{bmatrix} \begin{bmatrix} 1 \\ a \end{bmatrix} = \begin{bmatrix} SS_{p,\min} \\ 0_p \end{bmatrix}
\] (22)

These equations forms the normal equations of least squares analysis. This method is called Covariance method [13]. Even though \((X_p y) y^H X_p\) is the product of two Toeplitz matrices it is not Toeplitz, but this fact still makes it possible to develop a fast algorithm similar to that of the Levinson algorithm. In particular, the original fast algorithm to solve the covariance normal equations was developed by Morf et al. in [14], and further computational reduction was studied by Marple and reported in [9], producing an algorithm that requires \(o(p^3)\) operations.

**D. Burg Algorithm**

This is the most popular approach for AR parameter estimation with \(N\) data samples and was introduced by Burg in 1967 [15]. It may be viewed as a constrained least squares minimization.

The approach followed to estimate \(a_{p,k}\) consists of minimizing a sum of forward and backward linear prediction error energies, namely

\[
SS_p = \sum_{n=1}^{N-p} \left| e_p(n) \right|^2 = \sum_{n=p}^{N-1} a_{p,k} x_{n-k}^2 = E^H E.
\] (23)

where \(e_p(n)\) is defined by (14) and \(b_p(n)\) is called backward linear prediction error, whose expression is

\[
b_p(n) = \sum_{k=0}^{p} a_{p,k} x_{n-k+1} \quad \text{for } p \leq n \leq N-1.
\] (24)

Note that \(a_{p,0}\) is defined as unity. A close evaluation of (11) and (24) will show that the prediction error energy \(SS_p\) is function of the single parameter \(a_{p,p}\).

Substitution of (11) into (14) and (24) yields the following recursive relationship between the forward and backward prediction errors:

\[
e_p(n) = e_p(n-1) + a_{p,p} b_{p-1}(n) \quad \text{for } p \leq n \leq N-1
\] (25)

\[
b_p(n) = b_p(n) + a_{p,p} e_{p-1}(n+1) \quad \text{for } p \leq n \leq N-1
\] (26)

and substituting (25) and (26) into (23), \(SS_p\) can be written as

\[
SS_p = \Gamma_p + 2 a_{p,p} \Lambda_p + \Lambda_a a_{p,p}^2
\] (27)

whose coefficients are

\[
\Gamma_p = \sum_{n=1}^{N-p} \left| e_p(n) \right|^2 + \left| b_p(n-1) \right|^2
\] (28)

\[
\Lambda_p = 2 \sum_{n=1}^{N-p} e_p(n) b_{p-1}(n-1)
\] (29)

The value of \(a_{p,p}\) that minimize \(SS_p\) can be easily calculated setting the derivative to zero and obtaining:

\[
a_{p,p} = -\frac{\Lambda_p}{\Gamma_p}
\] (30)

Since the Levinson recursion is maintained in the Burg algorithm, then
The routine implemented to estimate the AR coefficients is sketched in Fig. 2. It needs an initializing step, in which the starting value of the observed forward and backward prediction errors and innovation variance are chosen using these relations:

$$e_0(n) = b_0(n) = x_n$$  \hspace{1cm} (32)

$$\sigma_0^2 = \frac{1}{N} \sum_{i=1}^{N} |x_i|^2.$$  \hspace{1cm} (33)

The Burg’s algorithm requires a number of operations proportional to $p^2$.

### E. Forward and Backward Linear Prediction Algorithm

This approach, proposed independently by Ulrych and Clayton [16] and Nuttal [17], is a least square procedure for forward and backward prediction, in which the Levinson constraint imposed by Burg is removed.

Noting that (14) and (24) can be summarized by

$$\Delta = \begin{bmatrix} E \\ B^T \end{bmatrix} = \begin{bmatrix} X_p \\ X_p^T J \end{bmatrix} \begin{bmatrix} a \end{bmatrix}$$  \hspace{1cm} (34)

where $B=[b_0(p),...,b_{(N-1)}]$ and $J$ is an $(p+1) \times (p+1)$ reflection matrix, and

$$X_p^T J = \begin{bmatrix} x_0^* & \cdots & x_p^* \\ \vdots & \ddots & \vdots \\ x_{N-p-1}^* & \cdots & x_{N-1}^* \end{bmatrix}$$  \hspace{1cm} (35)

is a Henkel matrix of conjugated data elements, it’s possible to rewrite (23) in this way

$$SS_p = \Delta^H \Delta = E^H E + B^H B.$$  \hspace{1cm} (36)

This formula can be minimized with the same procedure used for the covariance method leading to the set of normal equations

$$R_p \begin{bmatrix} 1 \\ a \end{bmatrix} = \begin{bmatrix} SS_{p,min} \\ 0 \end{bmatrix}$$  \hspace{1cm} (37)

in which

$$R_p = \begin{bmatrix} X_p^T X_p \\ X_p^T J \end{bmatrix} = X_p^H X_p + JX_p^T X_p J$$  \hspace{1cm} (38)

and the individual elements of $R_p$ have this form

$$r_p(i,j) = \sum_{s=0}^{X_{N-p-1}} (x_{s+p-j} x_{s+p-i} + x_{s+i} x_{s+j})$$ for $0 \leq i,j \leq p$.  \hspace{1cm} (39)

Because the summation range in (23) is identical to that of the covariance method, this least square approach is called the modified covariance method. In [16] and [17], all terms in the matrix (38) are directly computed, and the system (37) is solved through matrix inversion. This requires a number of operations proportional to $p^3$, which is one order of magnitude greater than Burg’s solution.

Thanks to the characteristic of the actual structure of the matrix (38), Marple in [11] and [9] suggests an algorithm requiring a number of computations proportional to $p^2$.

### III. OPTIMIZATION OF PSD ESTIMATION ALGORITHMS

As highlighted in the previous section, the performance of PSD AR estimators depends on the polynomial order $p$. To optimally choose this parameter a suitable simulation stage has been designed. A number of numerical tests have been executed in Matlab 7™ environment with the aim of minimizing the same figures of merit defined in [6],[7], and in particular:

a) the experimental standard deviation ($\sigma_C$) characterizing channel power measurement results;

b) the difference ($\Delta_C$) between the mean value of the channel power measurement results provided by the new algorithm and imposed one, considered as reference.

All the algorithms presented in Section II have been taken into account. The related Matlab implementations, available at the web site in [18], are optimized versions, in terms of computational burden, of those provided in [8].

DVB-T reference signals have firstly been generated according to the simulation procedure described in [6],[7].

The intermediate frequency has been set equal to 36.13 MHz, in order to meet the technical features of the downconversion circuitry the desired DSP-based meter is going to be equipped with. Philips TD1316ALF/IHP3™ tuner module for digital terrestrial application is, in particular, enlisted [19]. It is a high performance and cost effective single conversion tuner characterized by an IF center frequency of 36.13 MHz and a RF frequency range of 51-858 MHz. The following DVB-T transmission settings have been imposed: 8k transmission mode ($k$=6817 and $T_u$=896 μs), 1/4 ($\Delta$=224 μs) and 1/32 ($\Delta$=28 μs) guard intervals. In addition, three values of the oversampling factor (considered as the ratio between the
sample rate and IF signal central frequency) have been considered. The hypothesis of acquired records covering the time interval associated with 1/128 up to 1 DVB-T symbol has been held. For each transmission setting and oversampling factor value, 50 different realizations (test signals) have been produced. With special regard to AR estimation algorithms, taking into account that higher values of $p$ may introduce spurious details in the estimated spectrum, and lower values of $p$ may drive to a highly smoothed spectral estimate [10], a dual stage optimization procedure has been applied. In the first stage, a rough optimization has been pursued; in particular, a suitable operative range for $p$ has been fixed. The second stage has finely tuned the value of $p$, within the range previously determined, through the minimization of $\sigma_C$ and $\Delta C$.

A. Rough optimization

Suitable figures of merit, addressed to highlight the goodness of PSD estimates have been considered. The attention has been paid to FPE (Final Prediction Error), AIC (Akaike’s Information Criterion) and RMSE (Root Mean Square Error); details can be found in [10], [20].

Concerning $p$, two different and consecutive sets have been organized: $\Sigma_1 = \{p\mid 10 \leq p \leq 100\}$, $\Sigma_2 = \{p\mid 100 < p \leq 5000\}$. In $\Sigma_1$ an analysis step equal to 10 has been adopted, while a step equal to 100 has been considered for $\Sigma_2$.

All tests have highlighted quite the same performance of the three figures of merit; they have reached their minima in strictly overlapping $p$ ranges. For the sake of brevity, Fig. 3 shows only the minimum value of RMSE (Fig.3a) and the corresponding value of $p$ (Fig.3b) versus the observation period expressed as a fraction of the time interval associated with one DVB-T symbol, a guard interval equal to 224 $\mu$s and an oversampling factor equal to 3 are in particular enlisted. Very similar outcomes have been attained for a guard interval of 28 $\mu$s and oversampling factors equal to 6 and 12.

From the analysis of the results some considerations have emerged.

(i) Covariance, Burg and Modified Covariance estimators reach the lowest RMSE for very similar values of the polynomial order $p$.

(ii) RMSE values related to Covariance, Burg and Modified Covariance algorithms concur, showing comparable performance in PSD estimation.

(iii) The values of $p$ that minimize RMSE are significantly high for observation periods longer than 1/128 of the time interval associated with one DVB-T symbol.

To fix an operative range of $p$ of practical use, it has been held established that acceptable performance in channel power measurement can be assured in the presence of RMSE values lower than 3 dB (Fig 4). A threshold equal to 3 dB has been applied to the results already obtained, thus achieving a strong reduction of the values of $p$ of interest, with a consequent benefit to the computational burden.

B. Fine optimization

The stage has aimed at fixing the optimal value of $p$ within the operative range established before, and comparing the performance granted by the so-optimized Covariance, Burg and Modified Covariance estimator-based measurement algorithms to that assured by the WOSA estimator-based algorithm.

Since the results reported in [7] are related to an intermediate frequency equal to 21.4 MHz, a new optimization stage for the WOSA estimator-based algorithm has been carried out. The obtained outcomes completely concur with those already experienced in [7]; for the sake of brevity, they are not given here.
The obtained values of $\Delta_c$ and $\sigma_c$ and the polynomial order $p$ versus the observation period expressed as a fraction of the time interval associated with one DVB-T symbol, are presented in Fig. 5. An oversampling factor equal to 3 and a guard interval equal to 224 $\mu s$ have been considered. Very similar results have been experienced for a guard interval of 28 $\mu s$ and oversampling factors equals to 6 and 12.

It is possible to state that: (i) the considered AR algorithms grant very similar performance both for $\sigma_c$ and $\Delta_c$; (ii) the optimum polynomial order $p$ is equal to 46. In addition, the oversampling factor seems to have no influence; its lowest value (3) is advisable to reduce memory needs.

To fix the minimum hardware requirements of the DAS (Data Acquisition System) to be adopted in some experiments on emulated and actual DVB-T signals the results of which are described in section IV, further tests have been carried out. Table II gives the estimated $\sigma_c$ versus the analyzed values of ENOB (Effective Number Of Bits). Observation periods from 1/128 up to 1/4 of the time interval associated to one DVB-T symbol have been considered. $\sigma_c$ does not seem to be affected by vertical quantization, and Burg’s algorithm seems to be more stable if short observation periods are involved.

Computational burden, in terms of mean processing time on a common Pentium IV$^{TM}$ computer, has also been quantified. The results are given in Table III. It is possible to note that the measurement time peculiar to Burg estimator-based measurement algorithm is lower than those taken by Covariance and Modified Covariance estimator-based algorithms for short observation periods.

At the end, Burg estimator-based measurement algorithm has shown the best trade-off between metrological performance and measurement time. This is the reason why the Covariance and Modified Covariance estimator-based algorithms have no longer been considered in the subsequent stages of the work.

IV. PERFORMANCE ASSESSMENT

A. Tests with a real DAS

An emulation stage has been designed and executed with the aim of assessing the performance of the optimized Burg estimator-based measurement algorithm in the presence of a real DAS and comparing the obtained results to those furnished by the optimized WOSA algorithm. Moreover, all results have been compared to those assured by competitive measurement solutions already available on the market.

Stemming from the past experience [7], a suitable measurement station, sketched in Fig. 6, has been setup. It has included: (i) a control unit, namely a personal computer (PC); (ii) a RF signal generator equipped with DVB-T personalities, Agilent Technologies E4438C (250 kHz-6 GHz output frequency range); (iii) an express spectrum analyzer (ESA), Agilent Technologies E4402B (9 kHz-3 GHz input frequency range); (iv) a high performance spectrum analyzer (PSA), Agilent Technologies E4440A (3 Hz-26.5 GHz input

<table>
<thead>
<tr>
<th>Estimators</th>
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<th>6</th>
<th>7</th>
<th>8</th>
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<td>1.6</td>
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<td>1.5</td>
</tr>
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<td></td>
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<td>1.1</td>
<td>1.1</td>
<td>1.1</td>
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<tr>
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</tr>
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<td>0.26</td>
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</tr>
</tbody>
</table>
frequency range); (v) a real-time spectrum analyzer (RSA), Tektronix RSA3408A (DC-8 GHz input frequency range); (vi) a DAS LeCroy WavePro 7300A, (3 GHz bandwidth, 20 GS/s maximum sample rate) coupled to the aforementioned tuner module for digital terrestrial application. All instruments have been interconnected through an IEEE-488 standard interface bus. The function generator has provided 8 MHz bandwidth, DVB-T test signals, characterized by a RF center frequency equal to 610 MHz, a nominal total power of -10 dBm and a 64-QAM modulation scheme. Moreover, the same transmission settings considered in the previous stage have been imposed.

A preliminary characterization of cables and connectors utilized in the measurement station has been carried out through the vector network analyzer ANRITSU 37347C (40 MHz-20 GHz input frequency range), equipped with 3650 SMA 3.5 mm calibration kit, and the spectrum/network analyzer HP3589A respectively for RF and IF frequencies. The tuner has been characterized, too.

Different operative conditions of the DAS, in terms of vertical resolution (7 and 8 bit nominal) and observation period (from 1/128 up to 1/4 of the time interval associated with one DVB-T symbol), have been considered; the oversampling factor has been chosen equal to 3. For each of them, 100 sample records have been acquired and analyzed both through the Burg and WOSA estimator-based measurement algorithm.

The obtained results, given in Table IV, Table V and Table VI, have highlighted that:

- channel power measures provided by the Burg estimator-based measurement algorithm concur with those furnished by WOSA estimator-based algorithm;
- channel power measures are influenced by DAS vertical resolution both for Burg and WOSA estimator-based measurement algorithm;
- both algorithms exhibit satisfying and comparable repeatability, which is not affected by DAS vertical resolution and observation period;
- ESA and PSA outcomes concur with channel power measurement results of Burg and WOSA estimator-based measurement algorithm.

Measurement results of Burg and WOSA estimator-based measurement algorithms when a DAS resolution equal to 8 bits is adopted; a confidence level equal to 95% is considered;

- outcomes of the RSA operating both in normal conditions and as spectrum analyzer seem to concur with channel power measurement results of Burg and WOSA estimator-based algorithms only for a DAS resolution of 7 bits; a confidence level equal to 99% is considered.

### B. Experiments on real DVB-T signals

A number of experiments on real DVB-T signals have been carried out through the optimized algorithm. The signals have been radiated by one MEDIASET DVB-T multiplexer operating on the UHF 38 (610 MHz RF central frequency) channel.

A simplified measurement station has been adopted. With respect to that used in the emulation stage, the function generator has been replaced by a suitable amplified antenna.

<table>
<thead>
<tr>
<th>Table IV</th>
</tr>
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<tbody>
<tr>
<td>COMPARISON BETWEEN DIFFERENT ESTIMATION TECHNIQUES</td>
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<th>1/8</th>
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<th>1/32</th>
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<tr>
<td>Burg</td>
<td>0.062</td>
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<td>0.020</td>
<td>0.010</td>
<td>0.008</td>
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<td>Covariance</td>
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<td>0.018</td>
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<td>0.008</td>
<td>0.015</td>
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<td>Modified Covariance</td>
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<table>
<thead>
<tr>
<th>Figure of merit</th>
<th>Guard Interval [μs]</th>
<th>1/4</th>
<th>1/8</th>
<th>1/16</th>
<th>1/32</th>
<th>1/64</th>
<th>1/128</th>
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<tbody>
<tr>
<td>Pc [μW]</td>
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<td>106.41</td>
<td>106.39</td>
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<td>106.52</td>
<td>105.72</td>
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<tr>
<td></td>
<td>224</td>
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<td>104.83</td>
<td>104.71</td>
<td>104.68</td>
<td>104.08</td>
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<table>
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<th>7 bit DAS resolution</th>
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<tbody>
<tr>
<td>Observation period</td>
</tr>
<tr>
<td>Figure of merit</td>
</tr>
<tr>
<td>Pc [μW]</td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td>σc [μW]</td>
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<td></td>
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</table>
the PSA and RSA have been removed and a power splitter has been added [7]. Cables, connectors, and power splitter have been characterized through the aforementioned network analyzers.

Channel power measurement results are summarized in Table VII; good agreement can be appreciated.

### V. SUITABILITY OF BURG ESTIMATION IN A DSP-BASED METER

To quantify the convenience of adopting the Burg estimator in a cost-effective DSP-based meter, with respect to a WOSA-based solution, two figures of merit have been taken into account:

(i) memory requirement, intended as the minimum number of samples to be preserved in the meter memory;

(ii) computational burden, defined as the number of operations (real additions and real multiplications) to be performed for gaining the desired PSD.

**WOSA Estimator.** Let us consider an acquired sequence \( x(n), n=0,1,\ldots,N-1 \), and suppose to divide the acquired sequence in \( K \) overlapped segments, each of which \( M \) samples long. Let us define the overlap ratio, \( r \), as \( r = 100*N_p/M \% \), where \( N_p \) is the number of overlapped samples in each segment. The estimated PSD is expressed as

\[
S_i(f) = \frac{1}{K} \sum_{i=1}^{K} s_i(f)
\]

(40)

where \( s_i(f) \) is the modified periodogram of each segment.

It can be demonstrated that: (i) the memory of the meter has to be as deep as to preserve, for the whole measurement time, \( 2M \) real samples, related to the acquired and overlapped buffers, and \( 2M \) complex samples \((4M \) real samples) for the current and averaged FFT; considering a sampling time equal to \( T_s \), the meter has to perform the current FFT in a time interval (computational time) shorter than \( M^* (1-r)*T_s \), in order to prevent additional memory requirements; (ii) each FFT calculation, performed on \( M \) real samples, requires \( M^* \log_2(M) \) additions and \( M^* \log_2(M/2) \) multiplications. It is worth stressing that, to achieve a satisfying frequency resolution in PSD estimation, both \( K \) and \( M \) have to be sufficiently high, with a consequent increase of memory requirements and computational burden. As an example, let us consider that a DVB-T signal, with a center frequency of 36.13 MHz, is measured in 80 channels, and a FFT required for WOSA estimation is calculated on 4096 samples and requires 49152 additions and 45056 multiplications. To have a frequency resolution equal about to 24 kHz and an overlap ratio of 90%, the storage capability of the meter has to allow at least 24576 real samples to be preserved, and its computational time has to be not greater than 4.096 \( \mu \)s. The computational burden depends on the length of the acquired record.

**BURG Estimator.** Starting from what Kay and Marple have presented in [10], and considering the same acquired sequence described above, it is possible to demonstrate that: (i) the minimum number of samples to be stored is equal to \( 2N^p+2 \), where \( p \) is the selected polynomial order; (ii) \( 3Np^2-2Np \) real additions and \( 3Np^2-N+3p \) real multiplications are required for PSD estimation. For large values of \( N \), the computational burden is usually higher than that peculiar to the WOSA estimator. As for the computational time, the estimation of the current PSD has to take a time interval not greater than \( N^*T_s \), because the whole acquired sequence is involved.

In [10] it is also highlighted that the minimum length for the acquired sequence is \( 2p \), which means a memory requirement equal to \( 5p+2 \) (1502 samples to be stored for \( p = 300 \)), a computational burden of \( 2p^3-3p \) (179100 for \( p = 300 \)) real additions and \( 2p^2+p \) (180600 for \( p = 300 \)) real multiplications, and a computational time shorter than \( 2p^2*7\mu \)s (6 \( \mu \)s).

Even though the Burg estimator imposes a heavier

### TABLE V

<table>
<thead>
<tr>
<th>Figure of merit</th>
<th>Guard Interval [( \mu )s]</th>
<th>( P_c ) [( \mu )W]</th>
<th>( \sigma_c ) [( \mu )W]</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>1/4</td>
<td>1/8</td>
<td>1/16</td>
</tr>
<tr>
<td>PSA</td>
<td>28</td>
<td>106.63</td>
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</tr>
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<td></td>
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<td>0.63</td>
</tr>
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<td>PSA-SA</td>
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<td>224</td>
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</table>
computational burden with respect to WOSA one, its memory requirement is extremely advantageous, thus entitling it to be implemented in a cost-effective DSP-based meter.

VI. CONCLUSION

The first steps taken in the framework of a research activity aimed at the realization of a cost-effective DSP-based meter, for power measurements in DVB-T systems and apparatuses, have been accounted for. The attention has, in particular, been paid to the measurement algorithm to be adopted. Parametric autoregressive algorithms (Covariance, Burg and Modified Covariance) have thoroughly been optimized for the estimation both of PSD and channel power of DVB-T signals.

A number of tests conducted on simulated signals have shown that the Burg estimator based algorithm grants a good trade-off between computational burden and accuracy; negligible bias, good repeatability, and reasonable processing time have been experienced. Moreover, the results of several experiments on emulated DVB-T signals have given evidence of the concurrency of the results of the aforementioned algorithm with those provided by an alternative nonparametric solution (i.e. WOSA estimator-based measurement algorithm).

A separate section highlighting the suitability of using the Burg algorithm in a cost-effective DSP-based meter has also been given. It has been demonstrated that, even though the Burg estimator-based measurement algorithm imposes a heavier computational burden with respect to WOSA one, its memory requirement is extremely better. Further advantages could be gained if a sequential implementation, as defined in [9], is applied.

REFERENCES

[18] http://webuser.unicas.it/misure/DVBT/optimized
[19] Datasheet TD1300ATLI F mk3 Tuner modules for analog and digital terrestrial (OFDM) applications, available at www.nxp.com