Exercise 5.

Frequency Domain Analysis

Required knowledge

- Fourier-series and Fourier-transform.
- Measurement and interpretation of transfer function of linear systems.
- Transfer function of simple networks (first-order, high- and low-pass RC network).

Introduction

Signals are often represented in frequency domain by their spectrum, frequency, harmonic components, amplitude and phase. Time- and frequency-domain representations are mutually equivalent, and the Fourier transform can be used to transform signals between the two domains. Fourier transform exists for almost all practical signals which are used in electrical engineering practice. Frequency domain representation often simplifies the solution of several practical problems. It offers a compact and expressive form of signal representation by allowing the separation of spectral components. Frequency-domain representation can be effectively used in measurement of signal parameters, signal transmission, infocommunication, system design, etc.

One of the most important classes of signals is the class of periodic signals. Periodic signals are often used as excitation signals since they produce periodic signal with the same frequency at the output of the measured system. Periodic signals are easy to observe with simple instruments like oscilloscopes, moreover averaging can also be effectively used to increase the signal-to-noise ratio. System parameters can be determined by measuring the amplitude gain (or attenuation) and phase shift between the output and input. Fourier transform allows the characterization of systems in the simple form of a transfer function instead of convolution or differential equations connected to time-domain representation.

Aim of the Measurement

During the measurement, the students study the methods of signal analysis in frequency domain. They compare time domain algorithms to frequency domain ones. After finishing the measurement, they will be able to use frequency domain tools to describe properties of signals which cannot be easily detected in time-domain. During the laboratory students can apply their knowledge of signal and systems for solving engineering problems.

Theoretical background

Fourier series and Fourier transform

Real-valued periodic signals can be decomposed into linear combination of sine and cosine functions. This trigonometrical series is referred to as Fourier series of signals, and it has the following form (T stands for the period, and $\omega = 2\pi / T$ denotes the angular frequency):

$$u(t) = U_0 + \sum_{k=1}^{\infty} (U_k^A \cos k\omega t + U_k^B \sin k\omega t)\,, \tag{4-1}$$

where the coefficients can be calculated using the following equations:

$$U_0 = \frac{1}{T}\int_0^T u(t)dt\ ,\ U_k^A = \frac{2}{T}\int_0^T u(t)\cos(k\omega t)dt\ ,\ U_k^B = \frac{2}{T}\int_0^T u(t)\sin(\,k\omega t)dt\,. \tag{4-2}$$

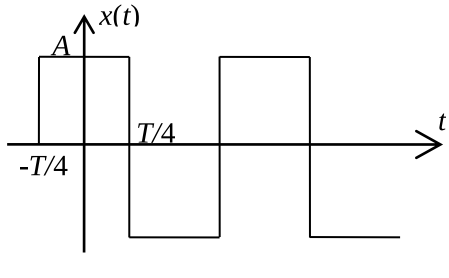
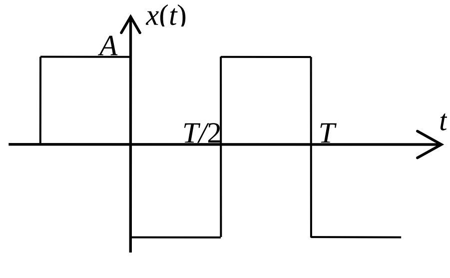
These operations are based on the orthogonality of trigonometric functions on the interval [0…T].

Fourier series have also a simpler form where complex-valued coefficients and complex exponential basis function are used:

$$u(t) = \sum_{k=-\infty}^{\infty} \overline{U}_k^C e^{jk\omega_0 t}\ \text{, where } \overline{U}_k^C = \frac{1}{T}\int_0^T u(t)e^{-jk\omega t}dt,\ \ k = 0, \pm 1, \pm 2... \tag{4-3}$$

For real-valued signals: $\overline{U}_k^C = \text{conjugate}\,(\overline{U}_{-k}^C)$, i.e., Fourier components form complex conjugate pairs.

The Fourier series of some practically important signals are summarized in the following table.

	
$x(t) = A\frac{4}{\pi}\left[\cos(\omega t) - \frac{1}{3}\cos(3\omega t) + \frac{1}{5}\cos(5\omega t) - ...\right]$	$x(t) = A\frac{4}{\pi}\left[\sin(\,\omega t) + \frac{1}{3}\sin(\,3\omega t) + \frac{1}{5}\sin(\,5\omega t) + ...\right]$
$U_k = \begin{cases} 0 & \text{if } k \text{ is even} \\ A\frac{4}{\pi}\left((-1)^{(k-1)/2}\frac{1}{k}\right) & \text{if } k \text{ is odd} \end{cases}$	$U_k = \begin{cases} 0 & \text{if } k \text{ is even} \\ A\frac{4}{\pi}\frac{1}{k} & \text{if } k \text{ is odd} \end{cases}$

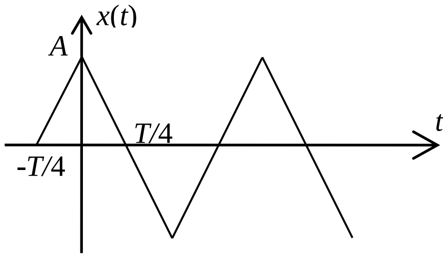
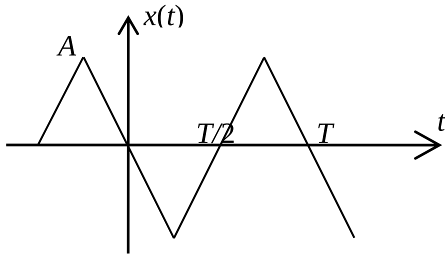
	
$x(t) = A\frac{8}{\pi}\left[\cos(\omega t) + \frac{1}{3^2}\cos(3\omega t) + \frac{1}{5^2}\cos(5\omega t) + ...\right]$	$x(t) = A\frac{8}{\pi}\left[\sin(\omega t) - \frac{1}{3^2}\sin(3\omega t) + \frac{1}{5^2}\sin(5\omega t) - ...\right]$
$U_k = \begin{cases} 0 & \text{if } k \text{ is even} \\ A\frac{8}{\pi^2}\frac{1}{k^2} & \text{if } k \text{ is odd} \end{cases}$	$U_k = \begin{cases} 0 & \text{if } k \text{ is even} \\ A\frac{8}{\pi^2}\left((-1)^{(k-1)/2}\frac{1}{k^2}\right) & \text{if } k \text{ is odd} \end{cases}$

Table 4-I. Fourier series of some periodic signals.

Fourier transform is the extension of Fourier series. It can be applied for square or absolute integrable functions. The spectrum of the signal $x(t)$ is obtained using the Fourier transform as follows:

$$X(j\omega) = \int_{-\infty}^{\infty} x(t)e^{-j\omega t}dt, \qquad (4\text{-}4)$$

The signal can be reconstructed from the spectrum $X(j\omega)$ as follows:

$$x(t) = \frac{1}{2\pi}\int_{-\infty}^{\infty} X(j\omega)e^{j\omega t}d\omega. \qquad (4\text{-}5)$$

The Fourier transform of some important signals such as Dirac impulse, step function, sine and other periodic functions is not convergent in classical sense since they are not square integrable functions. However, the Fourier transform of such signals can also be interpreted using the Dirac delta function. The Fourier transform of a complex exponential function $e^{j\omega t}$ is a Dirac delta at the frequency of the signal, so the Fourier transform of general periodic signals can be easily expressed using the Fourier series (4-3):

$$X(j\omega) = \sum_{k=-\infty}^{\infty} \overline{U}_k^C \delta(\omega - k\omega_0) \quad k = 0, \pm 1, \pm 2..., \qquad (4\text{-}6)$$

where ω_0 denotes the fundamental frequency of the periodic signal, $\delta(\omega - k\omega_0)$ denotes the Dirac delta function at the frequency $k\omega_0$. Dirac deltas are represented graphically as peaks at the frequencies where they are located. The spectrum (Fourier transform) of some typical periodic signals are illustrated in the following table.

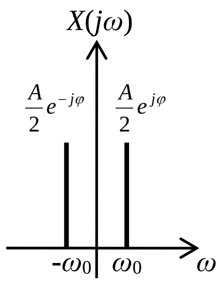
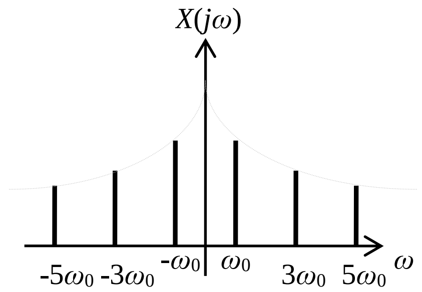
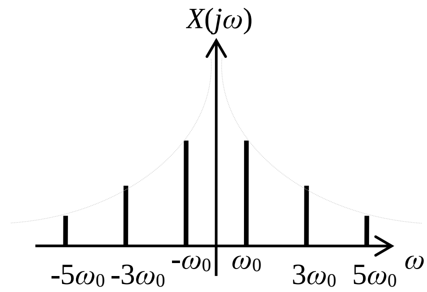
Spectrum of sine wave.	Spectrum of a square wave.	Spectrum of a triangle wave.
		
$x(t)=A\cdot\cos(\omega_0 t+\varphi)$ The spectrum contains only two complex conjugate spectral components at frequency $\pm\omega_0$.	Spectrum is decreasing with envelope $1/\omega$ (dotted line). Only odd components ($\pm\omega_0$, $\pm 3\omega_0$, $\pm 5\omega_0\ldots$) are present.	Spectrum is decreasing with envelope $1/\omega^2$ (dotted line). Only odd components ($\pm\omega_0$, $\pm 3\omega_0$, $\pm 5\omega_0\ldots$) are present.

Table 4-II. Fourier series of some periodic signals

It is important to note that it is not a general rule that the even harmonic components are missing from a periodic signal. For example, if the symmetry of a square wave differs from 50%, not only odd, but even spectral components appear.

Measurement of the spectrum by FFT

The integral (4-3) can be performed analytically for the above given, mathematically described signals, but this is often not the case for signals we are measuring. In this case, we only know the measured signal with a certain time resolution, since we had to sample the analog signal before numerical processing:

$$u[n] = u(n\Delta t), \tag{4-7}$$

where $\Delta t = 1/f_s$ is the sampling time, the reciprocal of the sampling rate or sampling frequency f_s. Accordingly, during the period time T we sample $N = T/\Delta t$ samples. The integral of Equation (4-3) can be approximated with a sum:

$$\overline{U}_k^C = \frac{1}{T}\int_0^T u(t)e^{-jk\omega_0 t}dt \approx \frac{1}{T}\sum_0^{N-1} u(n\Delta t)e^{-jk\frac{2\pi}{T}n\Delta t}\Delta t = \frac{1}{N}\sum_0^{N-1} u[n]e^{-jkn\frac{2\pi}{N}} \tag{4-8}$$

where we have used the fact that $\omega_0 = 2\pi/T$ and $\Delta t/T = 1/N$. Notice that the last formula is the definition of the Fourier series of a discrete-time signal, and the same sum without the *1/N* term is the DFT (Discrete Fourier Transform). So it is clear that if we want to know the Fourier components of a periodic signal, we can get them from the DFT of the signal samples by simple scaling with *1/N*.

The Agilent oscilloscope used in the lab has a built-in "FFT" function. Let's see what this means in practice! FFT is the abbreviation for Fast Fourier Transform, and is actually an algorithm efficiently implementing the DFT. Thus, the results of the FFT and DFT are equivalent. We also know that the instrument is designed to analyze periodic signals, so it does not actually display the DFT but the Fourier series values, i.e. it includes *1/N* scaling we described above. The complex Fourier series shows an amplitude of 0.5 V for a sine wave with a peak value of 1 V, since a sine signal with amplitude 1 is generated from a positive- and a negative-frequency complex exponential with amplitude 0.5. Therefore, to display the peak value of sine waves correctly, the values obtained by the Fourier series must be multiplied by two. However, the oscilloscope's instruction manual says that the instrument displays the amplitude of the sinusoidal components as 0 dB when their voltage is 1 V_{RMS}, which implies an additional scaling of $1/\sqrt{2}$, since the RMS value of a sine wave is $1/\sqrt{2}$ times compared to its amplitude. It can be concluded that the instrument scales the results of the FFT by a factor of $2/(\sqrt{2}N)$ before displaying it in dB scale.

When a spectrum analyzer is used to display the spectrum of a signal, generally one-sided spectrum is displayed, i.e., only the positive (right) frequency axis is shown (note that in Table 4-II both negative and positive frequency axes are displayed). This means no loss of information since the spectrum lines at the negative axis are the complex conjugates of the positive ones, so the amplitude spectrum is symmetric, and positive part is enough for most of the analysis.

Since digital oscilloscopes work on sampled signals, so sampling theorem should be hold, i.e., the bandwidth of the observed signal should be less than the half of the sampling frequency.

The spectrum is calculated from *N* time-domain samples, leading to *N* frequency points after FFT. Since the width of the computed spectrum equals the sampling frequency f_s, and this is divided to *N* points, each frequency point (or bin) represents a frequency range of $\Delta f = f_s / N$. This is the *resolution* of the DFT or FFT.

An important aspect of FFT-based spectrum analysis is that a real instrument can process samples of finite length. It is called windowing, i.e., the processing of finite number of samples of a signal means that we select a finite time window from the whole signal. Two phenomena result from this fact: *leakage* and *picket fence*. Leakage means that spectrum components may appear at such frequencies where no signal is present, and picket fence means that the amplitude of a signal obtained after FFT may smaller than its real amplitude.

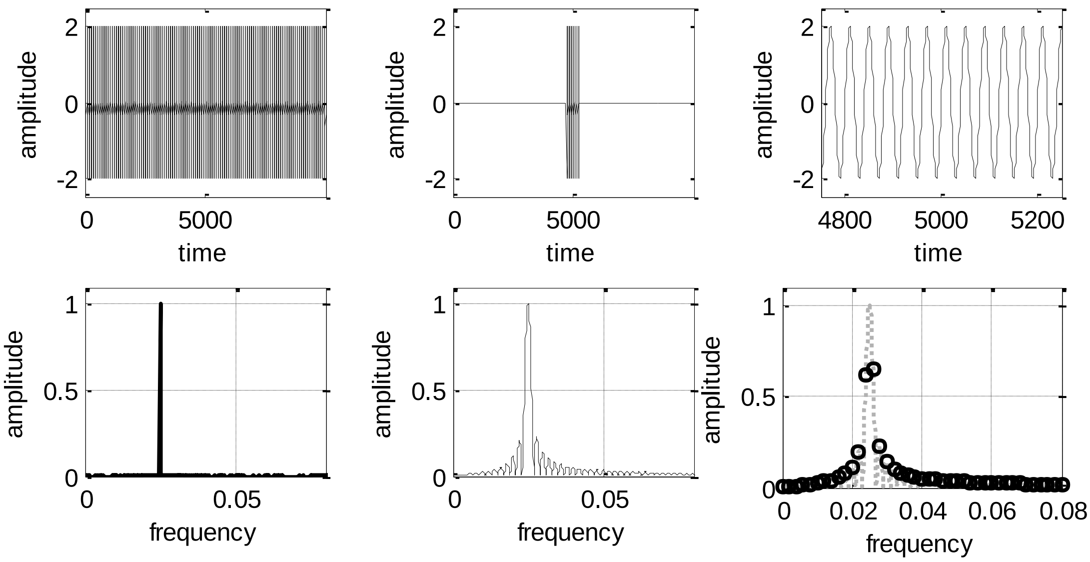


Figure 4–1. Illustration of the effect of windowing. The first row contains the time functions while the second row contains corresponding spectrums. Left column: ideal sine wave and its spectrum. Center column: the observed (windowed) part of a sine wave and its spectrum. Right column: the FFT of the observed signal. Circles indicate the spectrum calculated by FFT, the dotted line is the spectrum of the windowed signal. Both picket fence and leakage can be observed. The frequency of the signal is 0.025 Hz and sampling frequency is 1 Hz.

The complete explanation of the phenomenon of windowing is out of the scope of this guide but a short illustration of the leakage and picket fence can be seen in Fig. 4–10. for the case of a pure sine wave.

The left column of Fig. 4–1. shows the time function of a rather long observation of a sine wave (it is a good approximation of an infinite long observation). The spectrum is a spike at the frequency of the signal (0.025 Hz), as expected.

In the center column, a finite interval is selected from the time function. This operation can be mathematically modeled as if the signal were multiplied by a window function $w(t)$ which is zero where the signal is not observed and it is one where the signal can be observed. This kind of window function is called rectangular window. The spectrum of such a truncated sine wave is not a Dirac pulse, but the spectrum of the window function at the frequency of the sine wave (in the case of a rectangular window, it is a discrete sinc function). The reason is that multiplication in time domain corresponds to convolution in frequency domain: let the Fourier transform of the window function be $W(f)$ and the spectrum of the sine wave is $\delta(f-f_0)$, hence their convolution is $W(f)\times\delta(f-f_0) = W(f-f_0)$.

Finally, the FFT can be interpreted as if the continuous spectrum were sampled at discrete frequency values (it is a discrete Fourier transform). The values calculated by the FFT from the windowed signal are indicated by circles in the right column of Fig. 4–1 (these values are displayed on a spectrum analyzer). As one can see, in worst case the spectrum is calculated not at the peak of the windowed spectrum, so the peak value displayed by the spectrum analyzer is smaller than the peak value of the original spectrum. This phenomenon is called *picket fence*. The *leakage* can also be recognized in the figure, since the spectrum calculated by FFT contains nonzero values around the peak of the spectrum, where the spectrum of an ideal sine wave is zero.

The effect of picket fence and leakage can be reduced by applying different window functions before computing the FFT. There are several window functions, most commonly used windows are: *rectangular* window (basically, no windowing), *Hanning* window and *flat-top* window.

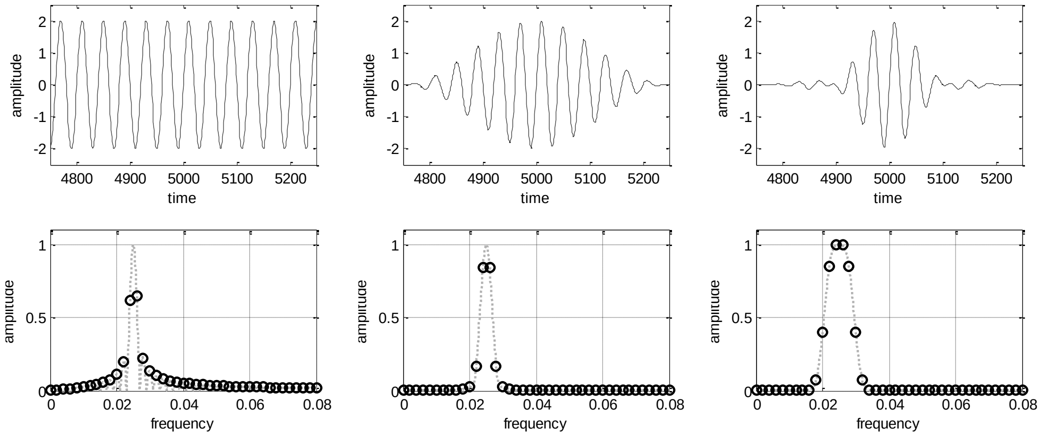


Figure 4–2. Spectrums with different window functions: rectangular, Hanning, flat-top. Frequency of the signal is 0.025 Hz and sampling frequency is 1 Hz.

Fig. 4–2. shows the spectrum of a sine wave with different window functions. The leakage is the largest in the case of the rectangular window. In the worst case, the amplitude of the signal read from the spectrum analyzer can be approximately 65% (approx. 4 dB) of the original amplitude (see left columns). In the case of a flat-top window (right column), the amplitude of the signal is displayed correctly, i.e., picket fence practically disappears, so it is advantageous when amplitude is measured. Its disadvantage is that the peak at the frequency of the sine wave becomes rather wide. A good trade-off is Hanning window which is often used for general investigations.

Let’s note that windowing occurs even we do not use it intentionally, but we process a data set of finite length without explicitly windowing it. In this case we use rectangular window implicitly.

It is also important to note that picket fence and leakage can disappear even for the case of using a rectangular window (in other words, when using no window at all) in the ideal case called *coherent sampling*. Coherent sampling means that we are observing integer periods of the periodic signal, meaning that the FFT is sampling the sinc function at its peak and zero crossings. This can be seen in Figure 4-3. left column, showing exactly one peak with correct frequency and amplitude. It can also be seen that in the case of coherent sampling widowing (being Hann or flat top window) does not improve the spectrum, but actually makes it worse, since the spectral peaks becomes wider. So in the ideal case whenever coherent sampling can be used - meaning that we can set the signal frequency or the spectrum analyzer such that the spectrum is computed from integer periods - no window function (or, rect window) should be used. Note however that this rarely happens in practice since we usually do not have any control over the frequency of the signal we are measuring. And for non-coherent sampling, where leakage and picket fence do occur for rectangular window, other window functions, such as Hann or flat top can decrease the measurement error.

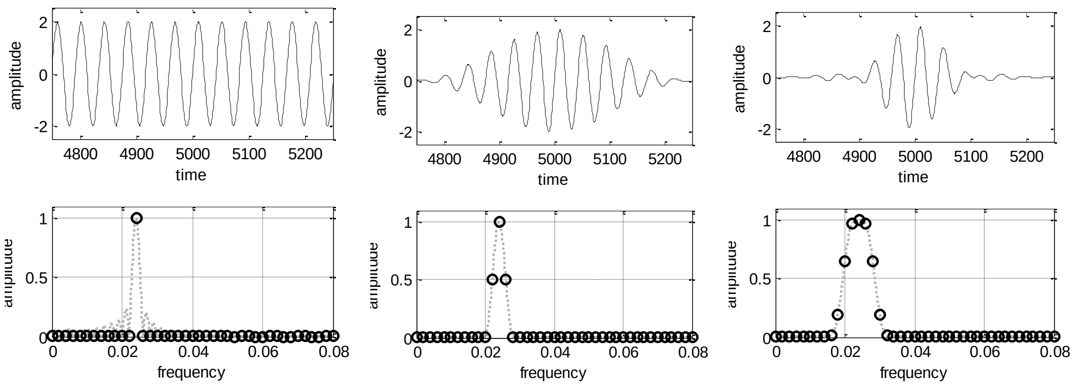


Figure 4–3. Spectrums with different window functions: rectangular, Hanning, flat-top. Frequency of the signal is 0.024 Hz and sampling frequency is 1 Hz. There is no picket fence and leakage.

Application of periodic signals as excitation signals

The most often used excitation signals are the sine wave and the square wave. In some applications, (e.g., measurement of static nonlinear characteristics) triangular or sawtooth waves are also used.

Square wave is often used as excitation signal since it is easy to generate even with simple circuits, and it can be used to measure the step response of a system. When a square wave is applied as an excitation signal, it is important that its half period should hold considerable longer (at least 5 or 10 times) than the largest time constant of the system to be investigated. In other words, the transient should vanish, and the steady state should be achieved before a new edge of the square wave. If this condition is fulfilled, the excitation signal can be regarded as a good approximation of a periodic step signal, so the response of the system can be regarded as its step response.

The shape of a signal in time domain allows us to make some important qualitative conclusions about its frequency-domain behavior. Since the square wave is not continuous (it contains steps at every level transition), so its spectrum is wide, i.e., it contains harmonic components of significant power in wide frequency range. It is an advantageous property when the square wave is used as excitation signal, since it excites the system in wide frequency range. Square wave is often used to test the frequency response of filters, amplifiers, etc. If the output of these systems is a clear square wave, then their transfer functions are frequency independent in a wide frequency range, so they cause small linear distortion on their input signals.

When an excitation signal is selected, both its time- and frequency-domain behavior should be considered. Some simple rules of thumb allow us to qualitatively determine the frequency-domain properties of a signal from its time-domain shape. The bandwidth of a signal is in close connection with its smoothness. The smoother a signal is, the faster its Fourier coefficients (or amplitude spectrum) tend to zero, i.e., its bandwidth is small. The smoothness of a signal is characterized by its derivative functions. Generally, if the k-th derivative of a function is not continuous, then its amplitude spectra decreases asymptotically as $|\omega|^{-(k+1)}$. For example, the square wave is not continuous, i.e., $k = 0$, so its spectrum decreases as $|1/\omega|$. The spectrum of the triangular wave tends to zero faster than that of the square wave, since it is a continuous function, and its first derivative is not continuous ($k = 1$), so its spectrum decreases with envelope $1/\omega^2$. Intuitively speaking, high frequency spectral components are required to generate steep slopes and discontinuities in a function. E.g., a triangular wave is “smoother” than a square wave, so its bandwidth is lower if their frequencies are identical.

Measurement of the transfer function

It is well known that a linear time-invariant system can change only the phase and amplitude of a sine wave applied to its input. Hence, the system can be characterized at each frequency by a complex number (complex gain) whose phase is the phase shift of the system, and its magnitude is the gain of the system. The transfer function is the complex gain of the linear system as function of frequency.

Several methods are known which allow the measurement of the transfer function of linear systems. In the following, some of these methods are summarized (the emphasis is put on the measurement of magnitude characteristics).

A well-known method of measurement of amplitude characteristics is performed using a sine wave generator and an AC multimeter that was done in laboratory measurement 2 “Time-domain measurement”. Its disadvantage is that the measurement is relatively time consuming, since the amplitude characteristics should be measured point-by-point along the whole frequency range.

In order to speed up the measurement, wideband signals and frequency selective instruments (like a spectrum analyzer or FFT analyzer) can be used to measure the entire amplitude characteristics in one step. Typical wideband excitation signals are multisine, swept sine (i.e., chirp), periodic sinc function, and noise.

The multisine is a periodic excitation signal which consists of the sum of sine waves with different frequencies. The frequencies are generally integral multiples of a fundamental frequency. The amplitudes of the sine wave components can be set to an arbitrary level, however, it is practical to set the levels of the sine components to the same value. The phases of the components should be set to different values (often randomly) in order to ensure small crest factor (crest factor = peak value / RMS value). A given measurement setup limits the peak value of the excitation signal in order to avoid saturation, so if the crest factor is small, the given peak value ensures high RMS value, i.e., good signal-to-noise ratio.

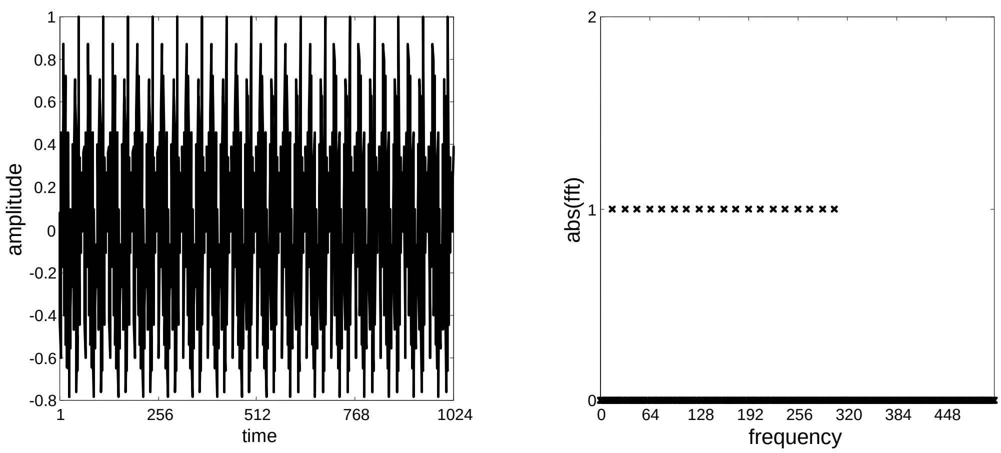


Figure 4–4. Multisine in time and frequency domain

The multisine is defined in time domain as follows:

$$x(t)=\sum_{k=1}^{F} A_k \sin\left(2\pi f_k t+\phi_k\right), \tag{4-9}$$

where F is the number of frequency components, and $f_k = k/T$, where T is the period of the multisine.

With the generator used in the lab, the random-phase multisine can only be achieved with cumbersome settings. Therefore we will use the periodic sinc function instead. The periodic sinc function is also a multisine, but here the components have not only the same amplitudes but also the same phases. This leads to a large crest factor which is not ideal for measurement, but as said, unfortunately the generator cannot do better with simple settings.

Since the Fourier transform of the sinc function is the rectangular window, the periodic sinc function is obtained from the sampling of the rectangular window, so that the amplitude of each harmonic is the same up to the sinc bandwidth and zero thereafter.

Nonlinear distortion

Nonlinear distortion is caused by systems whose output is not a linear function of their inputs. If this static nonlinear characteristics is approximated with its Taylor series, it is apparent that if a sinusoidal excitation signal is used, the output signal will contain spectral components not only at the fundamental frequency but also at integral multiple of it (at other harmonic frequencies). This phenomenon is called nonlinear distortion.

Several instruments (e.g., function generators, amplifiers) are often characterized by their nonlinear distortion. Distortion is mainly caused by the internal circuits of the instrument which results in the increase of spurious harmonic components. However, distortion may also occur using an incorrect measurement arrangement, e.g., by overdriving either the device under test or any of the instruments. The signal levels are often limited by the measurement range of the instrument and the supply voltage of the devices. Conversely, measurement range of an instrument (e.g., an oscilloscope) should be set every time such that no saturation is caused. In the figure below one can see a case when a sine wave is distorted, so its spectrum is contaminated by harmonic components. Frequency domain investigation is more suitable to detect distortion than time domain measurements, since the frequency selectivity of the spectrum analysis allows the detection even very small spurious spectral components that appear due to the distortion. The figure below shows that even a small distortion can cause the increase of harmonic components in the spectrum.

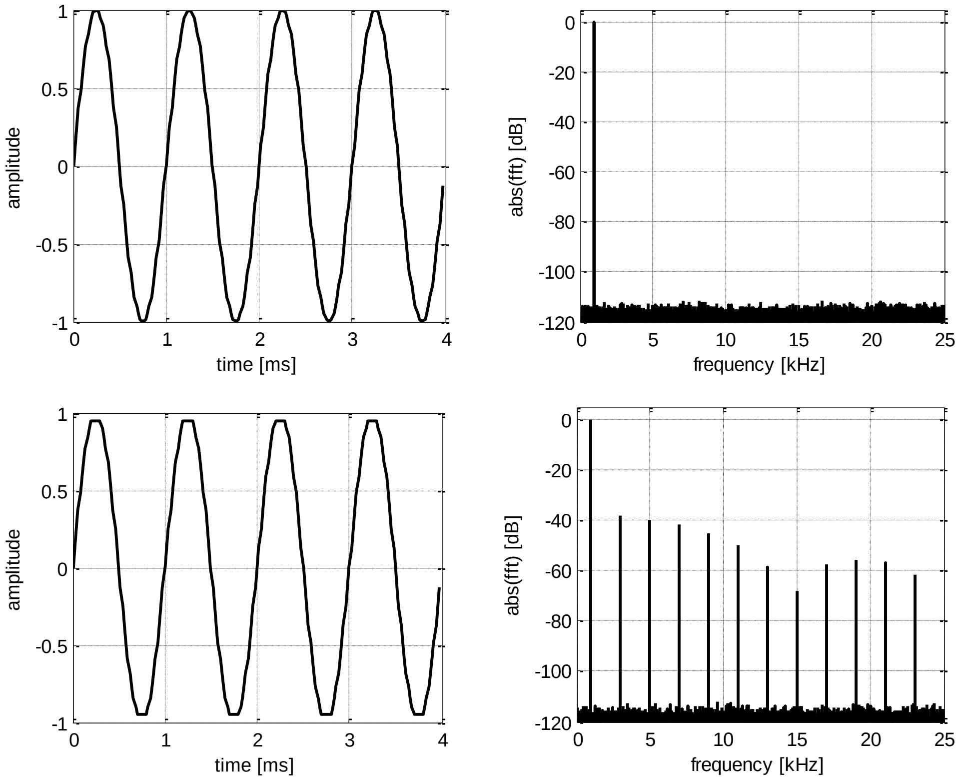


Figure 4–5. First row of graphs: undistorted sine wave (time function and spectrum); second row of graphs: distorted sine wave (saturation at 0.95). Parameters: 1 V amplitude, 1 kHz frequency, 50 kHz sampling frequency.

Distortion can be quantitatively characterized by the Total Harmonic Distortion (THD). Two definitions are also used to calculate THD:

$$k_1 = \sqrt{\frac{\sum_{i=2}^{\infty} X_i^2}{\sum_{i=1}^{\infty} X_i^2}}, \quad k_2 = \sqrt{\frac{\sum_{i=2}^{\infty} X_i^2}{X_1^2}}, \tag{4-10}$$

where X_i is the *i*-th harmonic component of the signal.

Web Links

http://en.wikipedia.org/wiki/Cutoff_frequency

http://en.wikipedia.org/wiki/Oscilloscope

http://en.wikipedia.org/wiki/Frequency_domain

http://en.wikipedia.org/wiki/Fourier_transform

Measurement Instruments

Digital multimeter	Agilent 34401A
Power supply	Agilent E3630
Function generator	Agilent 33220A
Oscilloscope	Agilent 54622A

Test Board

The board VIK-05-01 contains objects to be measured. The RC networks are configurable by allowing to select the resistance. The time constants for both the low- and high-pass networks are can be set by knobs.

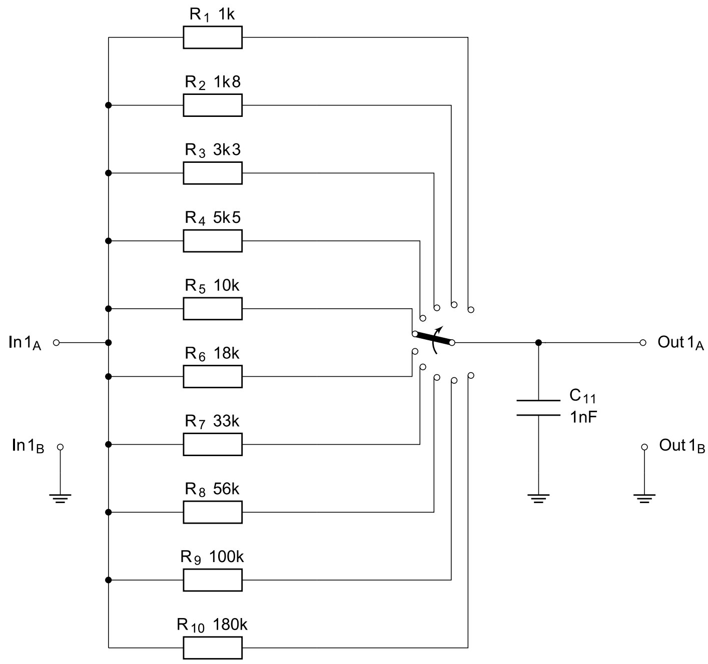


Figure 4–11. Circuit diagram of the variable first-order, low-pass filter

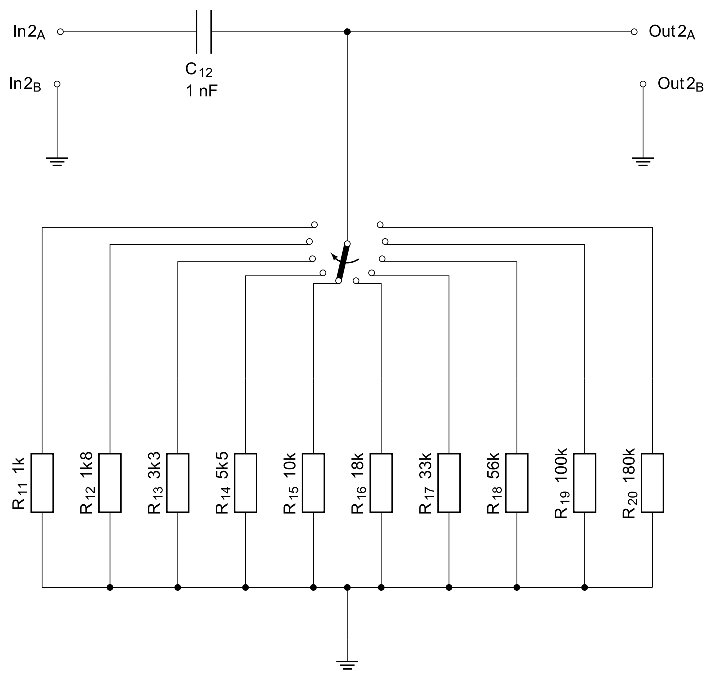


Figure 4–12. Circuit diagram of the variable first-order, high-pass filter

Additional remarks

Bandwidth

Every real measurement device has a finite input bandwidth, so does the oscilloscope. Within the bandwidth, input signals are handled unbiased. In the case of DC coupling the input characteristic can be modeled by a first-order, low-pass filter. The definition of the bandwidth is the frequency where the power has dropped by half (-3 dB). If the input signal contains frequency components larger than this, then the measured signal will be distorted. The error can be detected in both frequency (assuming that the device has FFT function) and time domains, because the FFT is based on time-domain measured data. In case of sine waves checking this condition is simple. However, before measuring complex signals (square, triangular signals) the frequency bandwidth which guarantees undistorted transfer has to be estimated.

Dynamic range

Applying frequency domain measurements two important parameters of the measurement devices have to be considered: bandwidth and dynamic range. The dynamic range is not equivalent with the resolution of the AD converter. The former gives the difference between the largest and smallest signals that can be measured. The later one defines the smallest step size. The smallest signal that can be measured is typically determined by the noise floor, which may coincide with error derived by resolution of the AD converter or may be greater because of analog noise sources or may be decreased by using averaging. The dynamic range of a common measurement device is 50-60 dB. In the case of a high quality spectrum analyzer it can be even 90 dB.

Sampling frequency

In digital devices the sampling frequency is one of the most important parameters. Unfortunately, the requirement in time domain differs from the requirement in frequency domain. Measurement in frequency domain needs only the sampling theorem to be fulfilled. For example, in the case of sine waves 4-5 samples from one period are well enough. In the case of time domain analysis more samples are necessary. To observe small changes in waves we should set the sampling frequency as high as possible. On the contrary, in frequency domain the frequency resolution should be increased. In the case of FFT analyzers distance between two adjacent frequencies (the resolution) depends on the size of FFT and the sampling frequency ($\Delta f = f_s / N$). According to the expression increasing the sampling frequency decreases the resolution. A good strategy in frequency domain analysis is when we decrease the sampling frequency as much as possible (until we still do not get aliasing) while we increase the size of FFT. It is worth noting that the device in the laboratory works with fixed size of FFT. Therefore, only the sampling frequency can be adjusted.

Test questions

1. How can be the frequency resolution of the DFT or FFT calculated based on the sampling rate and sample size?
2. What are the spectrums of the sine and square waves? At which frequencies can we find the components and what can we say about their amplitudes?
3. What happens to the spectrum of a sine wave when the input of the spectrum analyzer is overdriven?
4. What is the DFT of a periodic signal calculated from exactly ten periods of the signal?
5. What does it mean to sample a periodic signal coherently or non-coherently?
6. When measuring a sine wave, what are the undesirable effects of non-coherent sampling and how can we mitigate them?
7. What window function should be used for coherent sampling?
8. What are the advantages and disadvantages of using a flat top window?
9. What kind of excitation signals should be used if we aim to measure the frequency response (amplitude characteristic) of a system at multiple frequencies simultaneously?
10. How does the spectrum of a periodic sinc function look like? At which frequencies can we find the components and what can we say about their amplitudes?