

1.25-	
0.75- 0.5-	
0.25	0.65 1.3 1.95 2.6 25 3.9 4.55 5.2 5.85 6.5 <b>x</b> (t)
- 0.25 ¥ - 0.5 - - 0.75 -	
- 1- - 1.25-	
	t
	up to N=5 and change it to N=7 f x(t) gives a better representation of the signal x(t).
	e 4 peaks in the positive and negative sides instead of 3 when N=5.
Example 3	-3 Symbolic Computation of Fourier Series Same example as 3-2, but using the Mathcad Prime
	symbolic computation.
clear (x)	
$t := 0, \frac{\pi}{200}$	2• $\pi$ defining the range for time t
x (t) ≔    if	$(0 \le t \le 0)$ defining the function to be approximated $x \leftarrow 1$ approximated $(\pi \le t \le 2 \pi)$ $x \leftarrow -1$
    if	$x \leftarrow 1$ approximated $(\pi < 1 < 2 \pi)$
	$x \leftarrow -1$
T≔2 <i>π</i>	defining the fundamental period
$\omega_0 \coloneqq \frac{2 \pi}{T}$	
N := 6	defining the number of terms clear (n)
n≔16	set a range for n
$TOL := 10^{-1}$	<sup>-2</sup> reducing the tolerance
101-10	
	π 2π

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$$a_0 := \frac{2}{T} \cdot \int_0^{\infty} 1 \, dt + \frac{2}{T} \int_{\pi}^{\infty} -1 \, dt$$
  

$$a_0 \to 0 \qquad \text{calculate a0, arrow pointing to the right ---> calculate}$$

next defining a(n) and calculating

$$a(n) \coloneqq \frac{2}{T} \cdot \int_{0}^{\pi} \cos(n \cdot \omega_{0} \cdot t) dt + \frac{2}{T} \cdot \int_{\pi}^{2 \cdot \pi} (-1) \cos(n \cdot \omega_{0} \cdot t) dt \rightarrow \frac{\sin(\pi \cdot n)}{\pi \cdot n} + \frac{\sin(\pi \cdot n) - \sin(2 \cdot \pi \cdot n)}{\pi \cdot n}$$

next defining b(n) and calculating

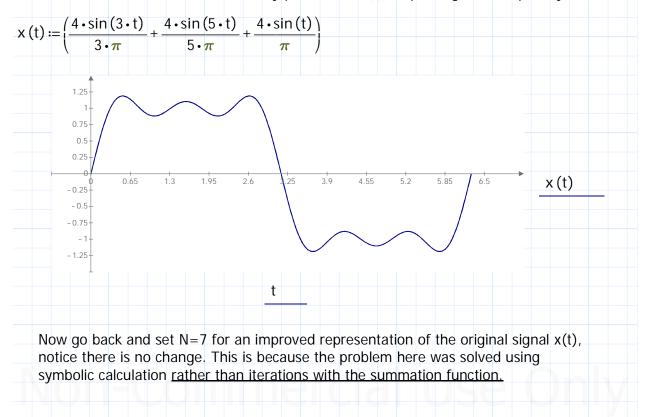
$$b(n) \coloneqq \frac{2}{T} \cdot \int_{0}^{\pi} \sin(n \cdot \omega_{0} \cdot t) dt + \frac{2}{T} \cdot \int_{\pi}^{2 \cdot \pi} (-1) \sin(n \cdot \omega_{0} \cdot t) dt \rightarrow \frac{2 \cdot \sin\left(\frac{\pi \cdot n}{2}\right)}{\pi \cdot n} - \frac{\cos(\pi \cdot n) - \cos(2 \cdot \pi \cdot n)}{\pi \cdot n}$$

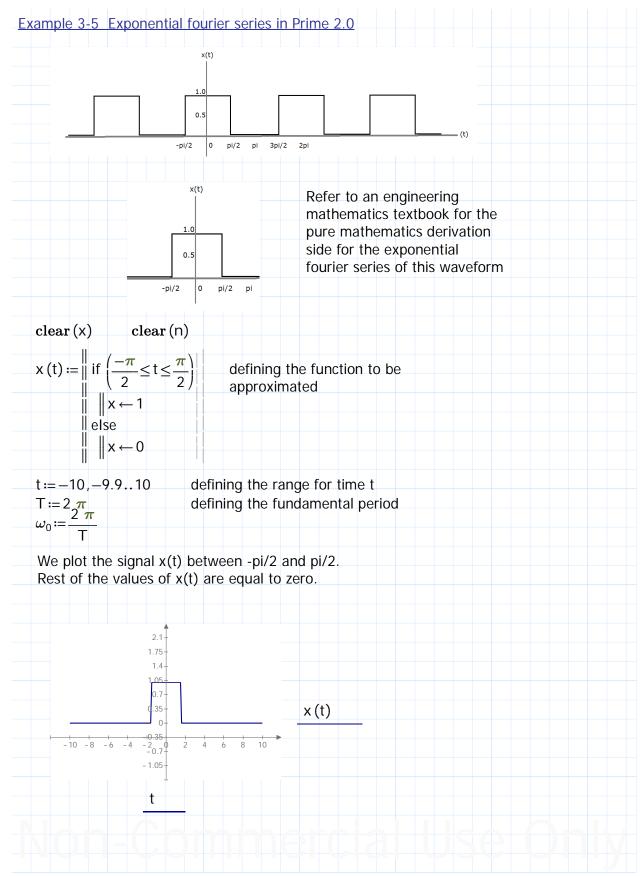
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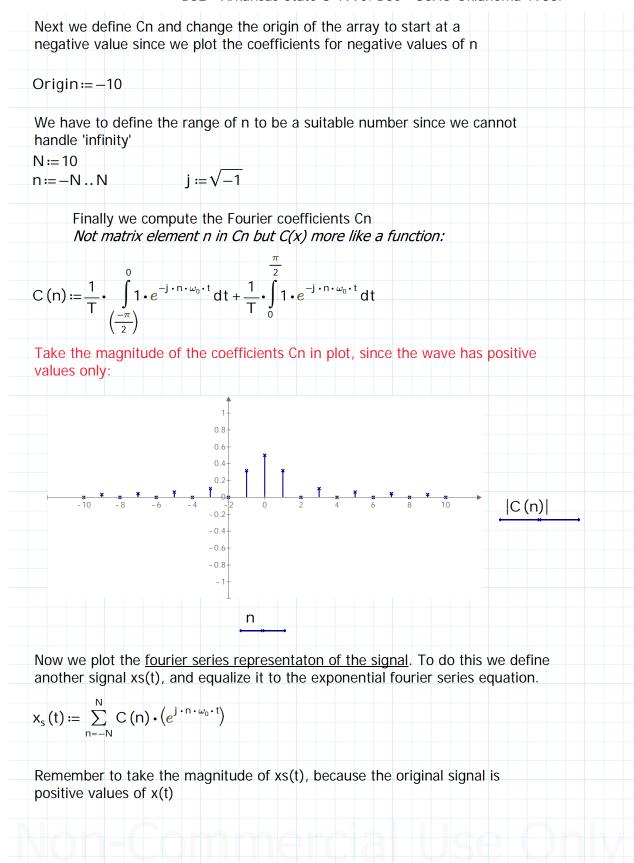
defining the fourier series equation and calculating

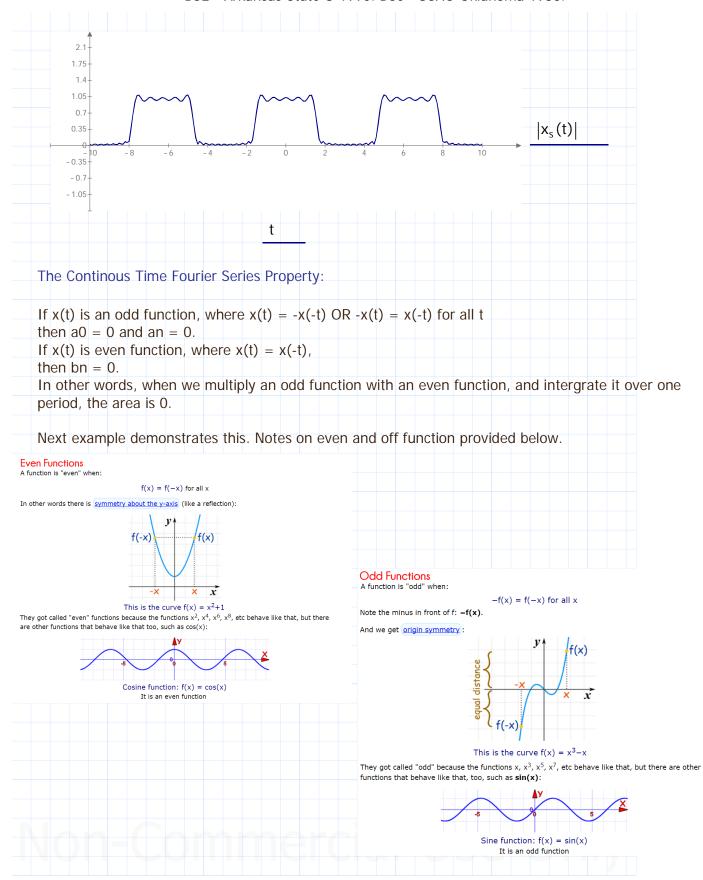
$$x(t) \coloneqq \frac{a_0}{2} + \left[ \sum_{n=1}^{N} \left( a(n) \cdot \cos(n \cdot \omega_0 \cdot t) + b(n) \cdot \sin(n \cdot \omega_0 \cdot t) \right) \right] \rightarrow \left[ \frac{4 \cdot \sin(3 \cdot t)}{3 \cdot \pi} + \frac{4 \cdot \sin(5 \cdot t)}{5 \cdot \pi} + \frac{4 \cdot \sin(t)}{\pi} \right]$$

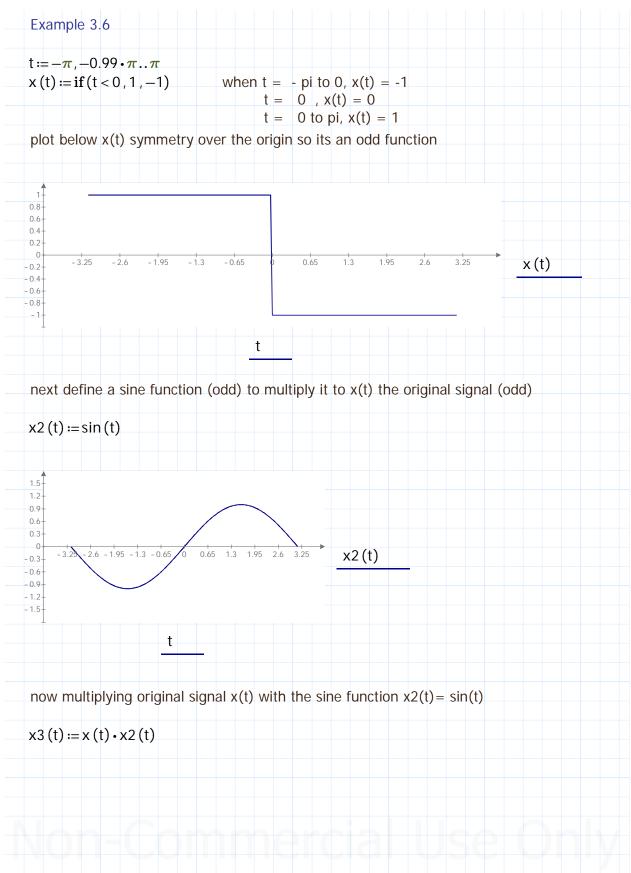
next for purpose of ploting manually set x(t) := to the evaluated answer above, the evaluated term above cannot be directly placed into x(t) for plotting into the plot's y-axis

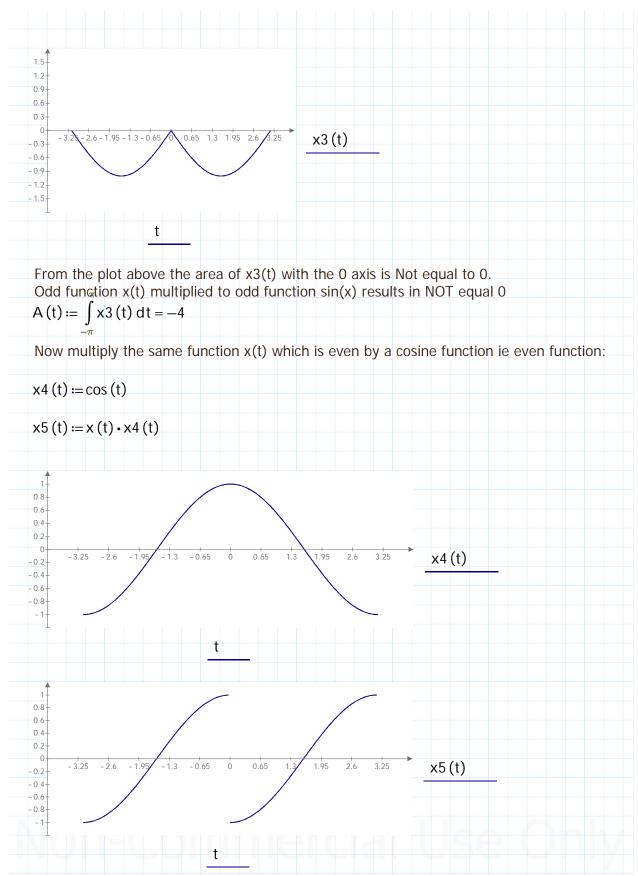


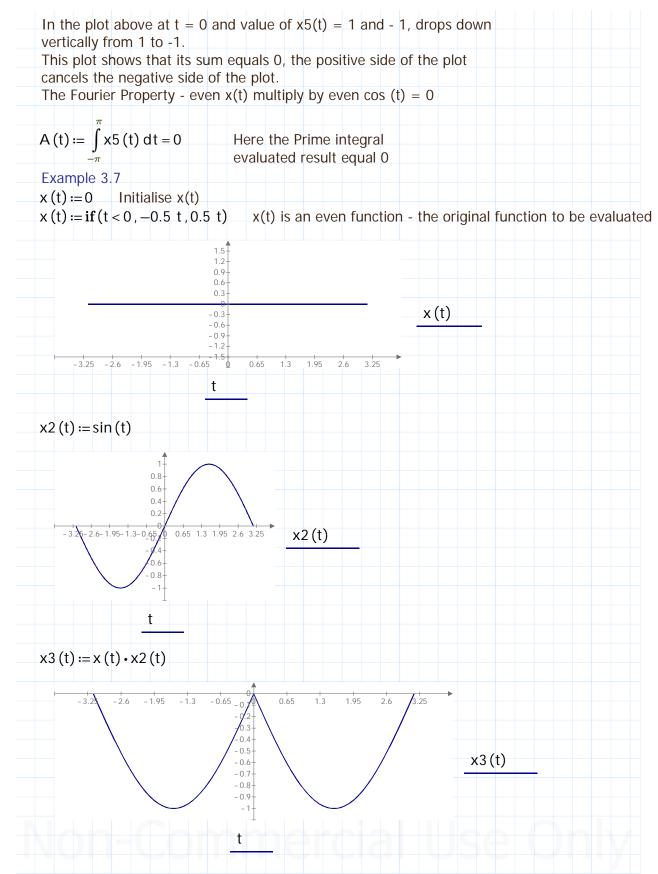


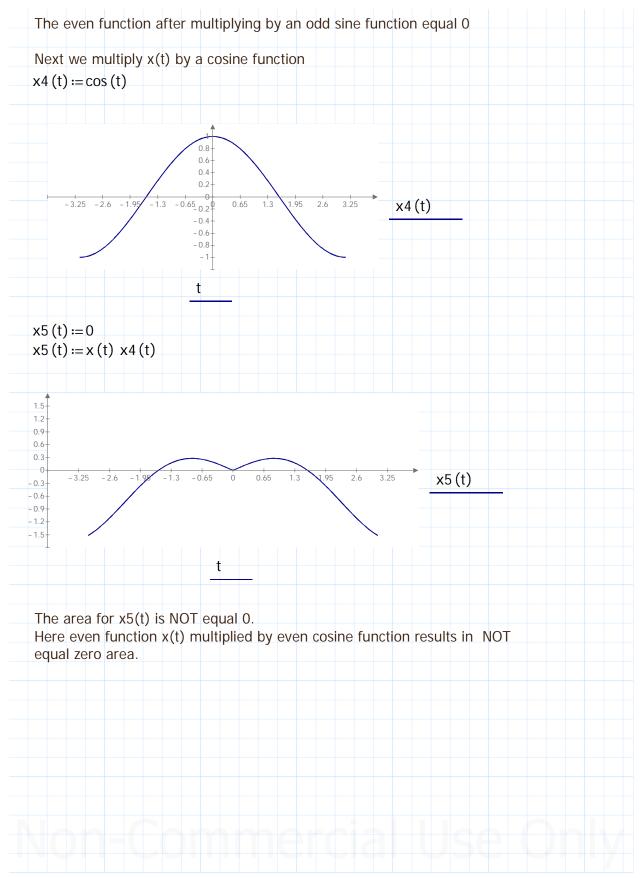












HAPTER

Chapter 3 Frequency Domain Analysis - Fourier Transform (FT), Inverse Fourier Transform and FT Spectra Entered by: Karl S Bogha Dhaliwal - Grad Cert Power Systems Protection and Relaying Uni of Idaho. USA. BSE - Arkansas State U 1990. BSc - USAO Oklahoma 1986.

The <u>Continous Time Fourier Transform</u> (Mixed explanation on this refer to your textbook, the objective is to get valuable results from Prime/Mathcad.

Notes from Chp 7 Linear Systems and Signals 2nd ed B.P. Lathi.

# Continuous-Time Signal Analysis: The Fourier Transform

We can analyze linear systems in many different ways by taking advantage of the property of linearity, where by the input is expressed as a sum of simpler components. The system response to any complex input can be found by summing the system's response to these simpler components of the input. In time-domain analysis, we separated the input into impulse components. In the frequency-domain analysis in Chapter 4, we separated the input into exponentials of the form  $e^{st}$  (the Laplace transform), where the complex frequency  $s = \sigma + j\omega$ . The Laplace transform, although very valuable for system analysis, proves somewhat awkward for signal analysis, where we prefer to represent signals in terms of exponentials  $e^{j\omega t}$  instead of  $e^{st}$ . This is accomplished by the Fourier transform. In a sense, the Fourier transform may be considered to be a special case of the Laplace transform with  $s = j\omega$ . Although this view is true most of the time, it does not always hold because of the nature of convergence of the Laplace and Fourier integrals.

In Chapter 6, we succeeded in representing periodic signals as a sum of (everlasting) sinusoids or exponentials of the form  $e^{j\omega t}$ . The Fourier integral developed in this chapter extends this spectral representation to aperiodic signals.

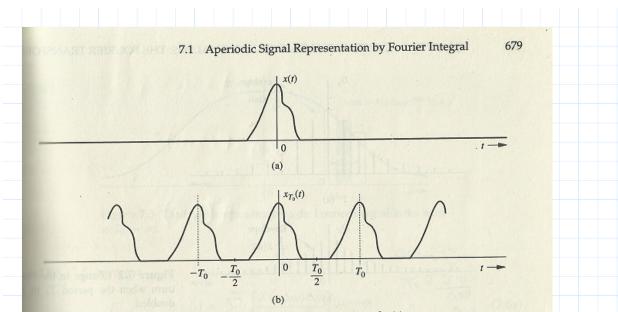
### 7.1 APERIODIC SIGNAL REPRESENTATION BY FOURIER INTEGRAL

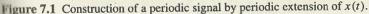
Applying a limiting process, we now show that an aperiodic signal can be expressed as a continuous sum (integral) of everlasting exponentials. To represent an aperiodic signal x(t) such as the one depicted in Fig. 7.1a by everlasting exponentials, let us construct a new periodic signal  $x_{T_0}(t)$  formed by repeating the signal x(t) at intervals of  $T_0$  seconds, as illustrated in Fig. 7.1b. The period  $T_0$  is made long enough to avoid overlap between the repeating pulses. The periodic signal  $x_{T_0}(t)$  can be represented by an exponential Fourier series. If we let  $T_0 \to \infty$ , the pulses in the periodic signal repeat after an infinite interval and, therefore

 $\lim_{T_0 \to \infty} x_{T_0}(t) = x(t)$ 

678

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Thus, the Fourier series representing  $x_{T_0}(t)$  will also represent x(t) in the limit  $T_0 \to \infty$ . The exponential Fourier series for  $x_{T_0}(t)$  is given by

$$x_{T_0}(t) = \sum_{n=-\infty}^{\infty} D_n e^{jn\omega_0 t}$$
(7.1)

where

$$D_n = \frac{1}{T_0} \int_{-T_0/2}^{T_0/2} x_{T_0}(t) e^{-jn\omega_0 t} dt$$
(7.2a)

$$v_0 = \frac{2\pi}{T_0} \tag{7.2b}$$

7.4)

Observe that integrating  $x_{T_0}(t)$  over  $(-T_0/2, T_0/2)$  is the same as integrating x(t) over  $(-\infty, \infty)$ . Therefore, Eq. (7.2a) can be expressed as

0

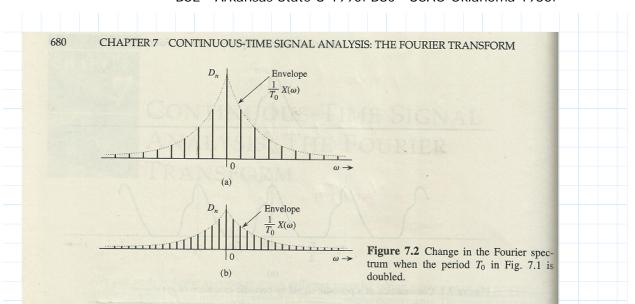
$$D_n = \frac{1}{T_0} \int_{-\infty}^{\infty} x(t) e^{-jn\omega_0 t} dt$$
 (7.2c)

It is interesting to see how the nature of the spectrum changes as  $T_0$  increases. To understand this fascinating behavior, let us define  $X(\omega)$ , a continuous function of  $\omega$ , as

A glance at Eqs. (7.2c) and (7.3) shows that

 $X(n\omega_0)$ 

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This means that the Fourier coefficients  $D_n$  are  $1/T_0$  times the samples of  $X(\omega)$  uniformly spaced at intervals of  $\omega_0$ , as depicted in Fig. 7.2a.<sup>†</sup> Therefore,  $(1/T_0)X(\omega)$  is the envelope for the coefficients  $D_n$ . We now let  $T_0 \to \infty$  by doubling  $T_0$  repeatedly. Doubling  $T_0$  halves the fundamental frequency  $\omega_0$  [Eq. (7.2b)], so that there are now twice as many components (samples) in the spectrum. However, by doubling  $T_0$ , the envelope  $(1/T_0)X(\omega)$  is halved, as shown in Fig. 7.2b. If we continue this process of doubling  $T_0$  repeatedly, the spectrum progressively becomes denser while its magnitude becomes smaller. Note, however, that the relative shape of the envelope remains the same [proportional to  $X(\omega)$  in Eq. (7.3)]. In the limit as  $T_0 \to \infty$ ,  $\omega_0 \to 0$  and  $D_n \to 0$ . This result makes for a spectrum so dense that the spectral components are spaced at zero (infinitesimal) intervals. At the same time, the amplitude of each component is zero (infinitesimal). We have nothing of everything, yet we have something! This paradox sounds like Alice in Wonderland, but as we shall see, these are the classic characteristics of a very familiar phenomenon.<sup>‡</sup>

Substitution of Eq. (7.4) in Eq. (7.1) yields  $\chi(x,y)$ 

$$T_{p}(t) = \sum_{k} D_{n} e^{j n w_{0} t}$$

×

5)

As  $T_0 \to \infty$ ,  $\omega_0$  becomes infinitesimal ( $\omega_0 \to 0$ ). Hence, we shall replace  $\omega_0$  by a more appropriate notation,  $\Delta \omega$ . In terms of this new notation, Eq. (7.2b) becomes

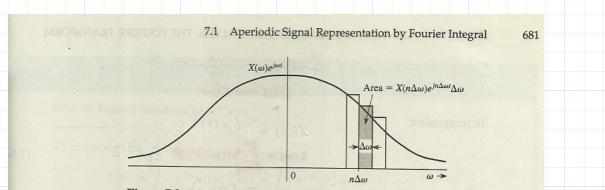
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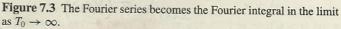
$$\omega = \frac{2\pi}{T_0} \quad V$$

<sup>1</sup>For the sake of simplicity, we assume  $D_n$ , and therefore  $X(\omega)$ , in Fig. 7.2, to be real. The argument, however, is also valid for complex  $D_n$  [or  $X(\omega)$ ].

<sup>t</sup>If nothing else, the reader now has irrefutable proof of the proposition that 0% ownership of everything is better than 100% ownership of nothing.

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and Eq. (7.5) becomes

x

$$T_{0}(t) = \sum_{n=-\infty}^{\infty} \left[ \frac{X(n\Delta\omega)\Delta\omega}{2\pi} \right] e^{(jn\Delta\omega)t} \qquad \begin{array}{c} T_{0} = \frac{2\pi}{\Delta\omega} \\ \vdots \\ T_{0} = \frac{\Delta\omega}{2\pi} \end{array}$$
(7.6a)

DW=27

Equation (7.6a) shows that  $x_{T_0}(t)$  can be expressed as a sum of everlasting exponentials of frequencies  $0, \pm \Delta \omega, \pm 2\Delta \omega, \pm 3\Delta \omega, \ldots$  (the Fourier series). The amount of the component of frequency  $n\Delta \omega$  is  $[X(n\Delta \omega)\Delta \omega]/2\pi$ . In the limit as  $T_0 \to \infty, \Delta \omega \to 0$  and  $x_{T_0}(t) \to x(t)$ . Therefore

$$\begin{aligned} z(t) &= \lim_{T_0 \to \infty} x_{T_0}(t) \\ &= \lim_{\Delta \omega \to 0} \frac{1}{2\pi} \sum_{n = -\infty}^{\infty} X(n\Delta\omega) e^{(jn\Delta\omega)t} \Delta\omega \end{aligned}$$
(7.6b)

The sum on the right-hand side of Eq. (7.6b) can be viewed as the area under the function  $X(\omega)e^{j\omega t}$ , as illustrated in Fig. 7.3. Therefore

$$x(t) = \frac{1}{2\pi} \int_{-\infty}^{\infty} X(\omega) e^{j\omega t} d\omega$$
(7.7)

The integral on the right-hand side is called the *Fourier integral*. We have now succeeded in representing an aperiodic signal x(t) by a Fourier integral (rather than a Fourier series).<sup>†</sup> This integral is basically a Fourier series (in the limit) with fundamental frequency  $\Delta \omega \rightarrow 0$ , as seen from Eq. (7.6). The amount of the exponential  $e^{jn\Delta\omega t}$  is  $X(n\Delta\omega)\Delta\omega/2\pi$ . Thus, the function  $X(\omega)$  given by Eq. (7.3) acts as a spectral function.  $X(\omega) = \sum_{i=1}^{\infty} \frac{1}{i} \frac$ 

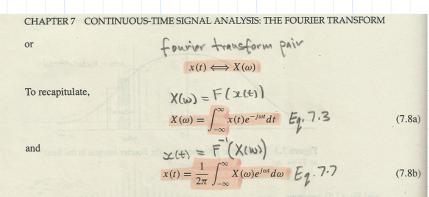
of  $X(\omega)$ . The same information is conveyed by the statement that x(t) and  $X(\omega)$  are a Fourier transform pair. Symbolically, this statement is expressed as

 $X(\omega) = \mathcal{F}[x(t)]$  and  $x(t) = \mathcal{F}^{-1}[X(\omega)]$ 

<sup>†</sup>This derivation should not be considered to be a rigorous proof of Eq. (7.7). The situation is not as simple as we have made it appear.<sup>1</sup>

32

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It is helpful to keep in mind that the Fourier integral in Eq. (7.8b) is of the nature of a Fourier series with fundamental frequency  $\Delta \omega$  approaching zero [Eq. (7.6b)]. Therefore, most of the discussion and properties of Fourier series apply to the Fourier transform as well. <u>The transform</u>  $X(\omega)$  is the frequency-domain specification of x(t).

We can plot the spectrum  $X(\omega)$  as a function of  $\omega$ . Since  $X(\omega)$  is complex, we have both amplitude and angle (or phase) spectra

$$X(\omega) = |X(\omega)|e^{j \angle X(\omega)}$$
(7.9)

in which  $|X(\omega)|$  is the amplitude and  $\angle X(\omega)$  is the angle (or phase) of  $X(\omega)$ . According to Eq. (7.8a),

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

Taking the conjugates of both sides yields

$$x^*(t) \Longleftrightarrow X^*(-\omega) \tag{7.10}$$

This property is known as the *conjugation property*. Now, if x(t) is a real function of t, then  $x(t) = x^*(t)$ , and from the conjugation property, we find that

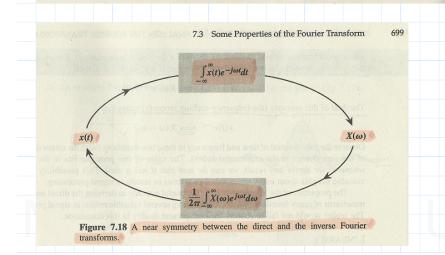
$$X(-\omega) = X^*(\omega) \tag{7.11a}$$

This is the <u>conjugate symmetry</u> property of the Fourier transform, applicable to real x(t). Therefore, for real x(t)

$$|X(-\omega)| = |X(\omega)| \tag{7.11b}$$

$$\angle X(-\omega) = -\angle X(\omega) \tag{7.11c}$$

Thus, for real x(t), the amplitude spectrum  $[X(\omega)]$  is an even function, and the phase spectrum  $\mathcal{L}X(\omega)$  is an odd function of  $\omega$ . These results were derived earlier for the Fourier spectrum of a periodic signal [Eq. (6.33)] and should come as no surprise.



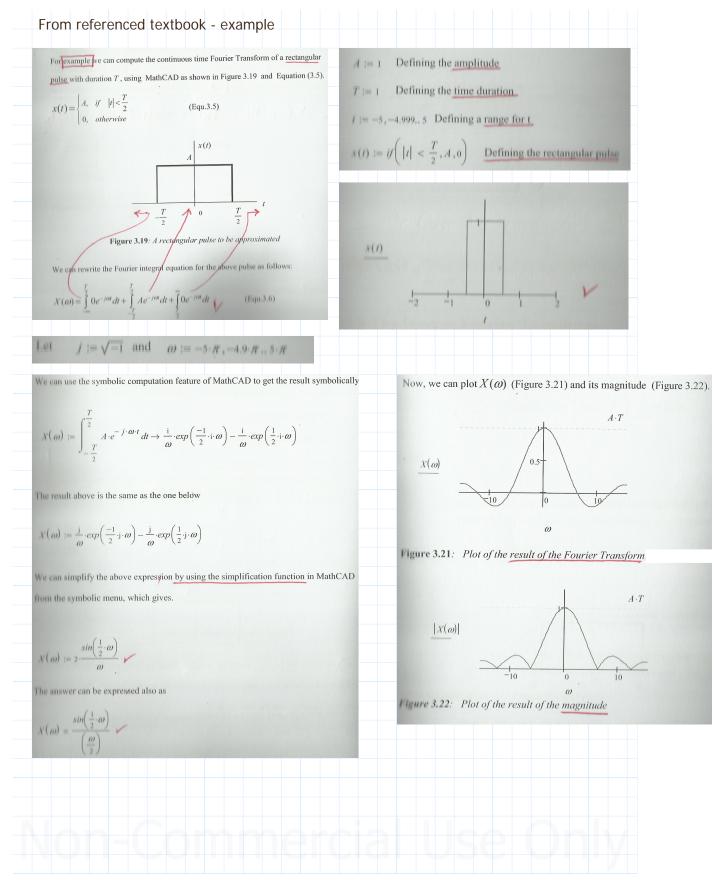
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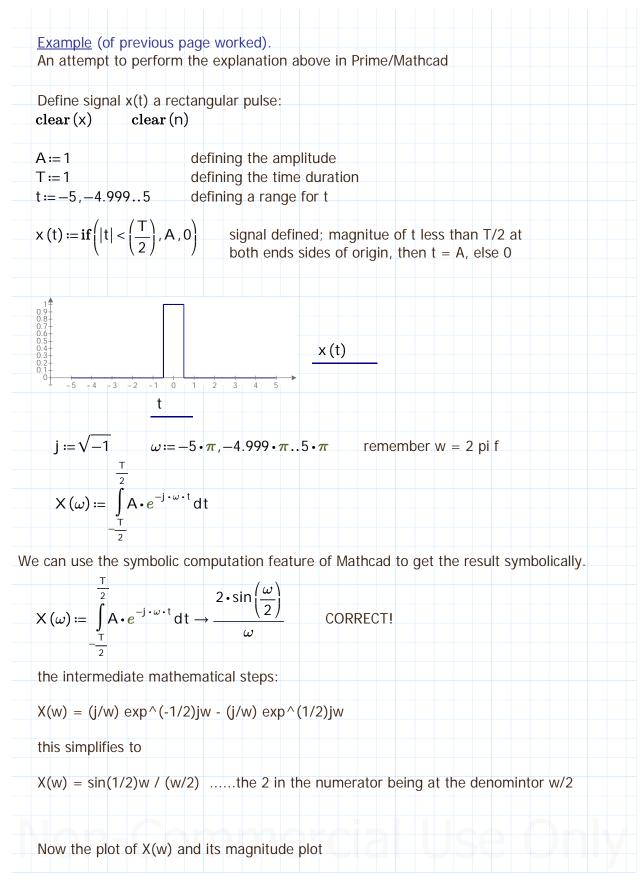
		7.1 Fourier Trans		
<u>1</u> 93	lo.	<i>x</i> ( <i>t</i> )	$X(\omega)$	
	1.1.00	$e^{-at}u(t)$	$\frac{1}{a > 0}$	
		Tan.	$a + j\omega$	1
:	2	$e^{at}u(-t)$	$\frac{1}{a-j\omega} \qquad \qquad a>0$	
	3	$e^{-a t }$	$\frac{2a}{a^2 + \omega^2} \qquad \qquad a > 0$	
when	4	4 == al = (A)	we can be sure that it has a didt. This possibility can	
VEIGH	+	$te^{-at}u(t)$	$\overline{(a+j\omega)^2} \qquad \qquad a>0$	
franct	5	$t^n e^{-at} u(t)$	$\frac{n!}{(a+j\omega)^{n+1}} \qquad a>0$	1
The re	ader of		$\overline{(a+j\omega)^{n+1}} \qquad \qquad a>0$	
	6	$\delta(t)$	1	
LINE	7	1	$2\pi\delta(\omega)$	
	8	$e^{j\omega_0 t}$	$2\pi\delta(\omega-\omega_0)$	1
	9	$\cos \omega_0 t$	$\pi[\delta(\omega-\omega_0)+\delta(\omega+\omega_0)]$	
10	0.	$\sin \omega_0 t$	$j\pi[\delta(\omega+\omega_0)-\delta(\omega-\omega_0)]$	
1	1	<i>u</i> ( <i>t</i> )	$\pi\delta(\omega) + \frac{1}{i\omega}$	
12	2	sgn t	$\frac{2}{j\omega}$	
1 Ennie				
13	3	$\cos \omega_0 t u(t)$	$\frac{\pi}{2}[\delta(\omega-\omega_0)+\delta(\omega+\omega_0)]+\frac{j\omega}{\omega_0^2-\omega^2}$	
14	4	$\sin \omega_0 t  u(t)$	$\frac{\pi}{2j}[\delta(\omega-\omega_0)-\delta(\omega+\omega_0)]+\frac{\omega_0}{\omega_0^2-\omega^2}$	
1:	5	$e^{-at}\sin\omega_0 t u(t)$	$\frac{\omega_0}{(a+j\omega)^2 + \omega_0^2} \qquad \qquad a > 0$	
		Real Property and		
10	5	$e^{-at}\cos\omega_0 t u(t)$	$\frac{a+j\omega}{(a+j\omega)^2+\omega_0^2} \qquad \qquad a>0$	1
15 7 (4		(1)		
17	7	$\operatorname{rect}\left(\frac{t}{\tau}\right)$	$\tau \operatorname{sinc}\left(\frac{\omega \tau}{2}\right)$	1
18	8	$\frac{W}{\pi}$ sinc (Wt)	$\operatorname{rect}\left(\frac{\omega}{2W}\right)$	
19		$\Delta\left(\frac{t}{\tau}\right)$	$\frac{\tau}{2}\operatorname{sinc}^2\left(\frac{\omega\tau}{4}\right)$	
	fm al	the sourced (a) in	In the (T 33) manufact had been and (FF T) off at	
20	the rol	$\frac{w}{2\pi}\operatorname{sinc}^2\left(\frac{w}{2}\right)$	$\Delta\left(\frac{\omega}{2W}\right)$	1
		~ ( ~ )	with the mane adjustment of the factor of the many	
21		$\sum  \delta(t-nT)$	$\omega_0 \sum_{n=-\infty}^{\infty} \delta(\omega - n\omega_0) \qquad \qquad \omega_0 = \frac{2\pi}{T}$ $\sigma \sqrt{2\pi} e^{-\sigma^2 \omega^2/2}$	
22		n=-∞		

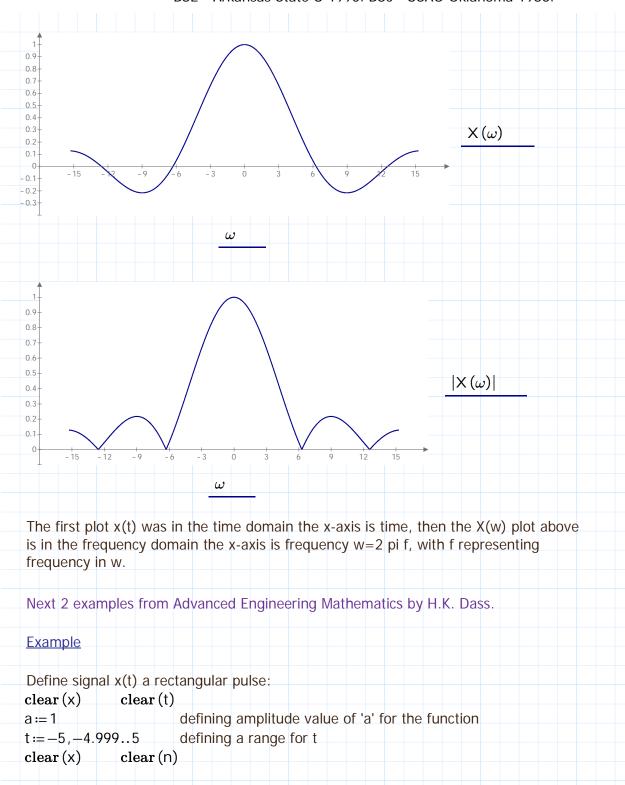
Fourier transform is used to approximate aperiodic signals from time to frequency domains. For instance, a single pulse with duration T can be approximated by using the Fourier Transform.

The fourier transform of an aperiodic signal is defined as:

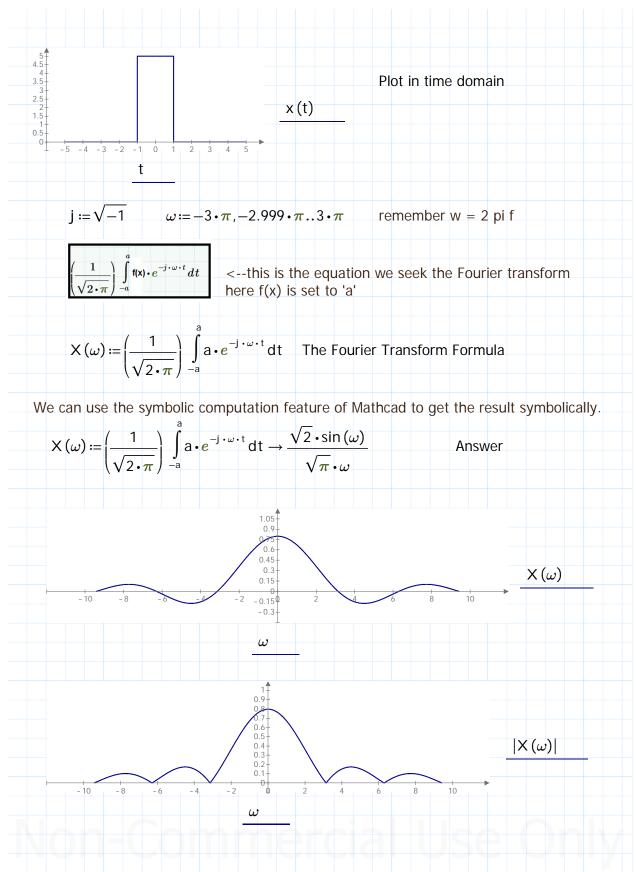
n -jwt	
$X(w) = \int x(t)e^{-jwt} dt$	A signal that is not periodic is called an aperiodic signal

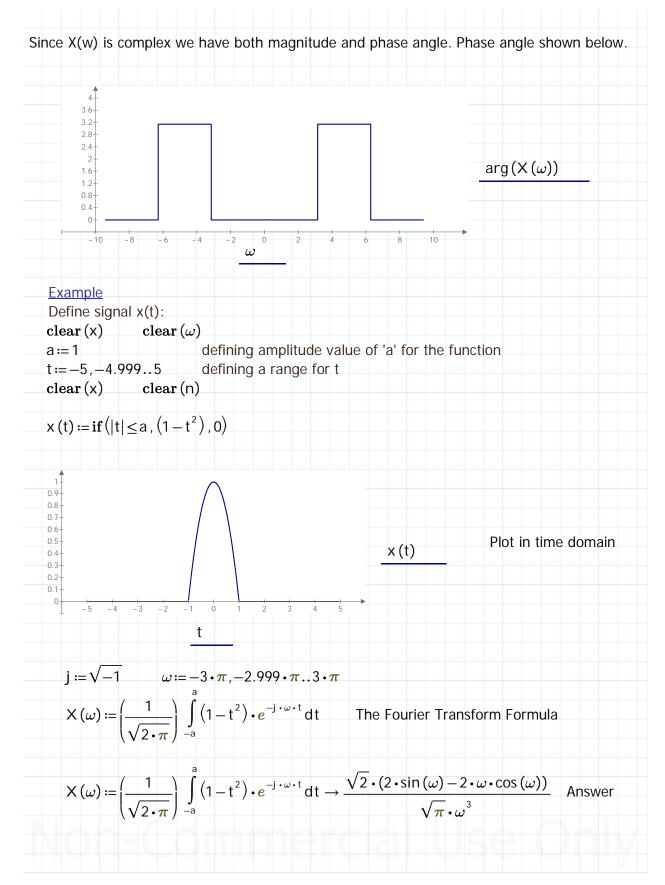


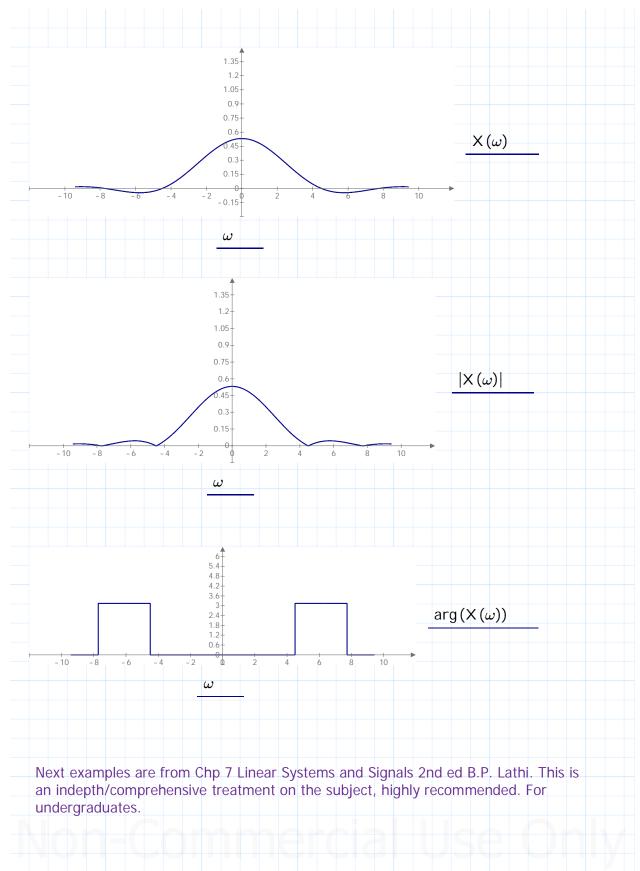


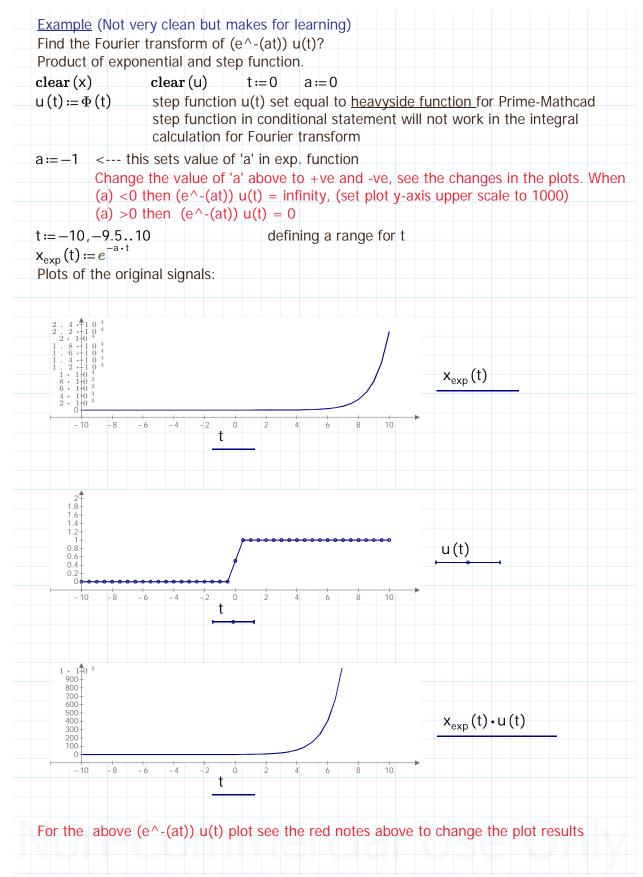


x(t) := if( t  < a, 5, 0)	defining the function to be approximated
	its equal to 1 when  t  <a, 0,<="" else="" th=""></a,>









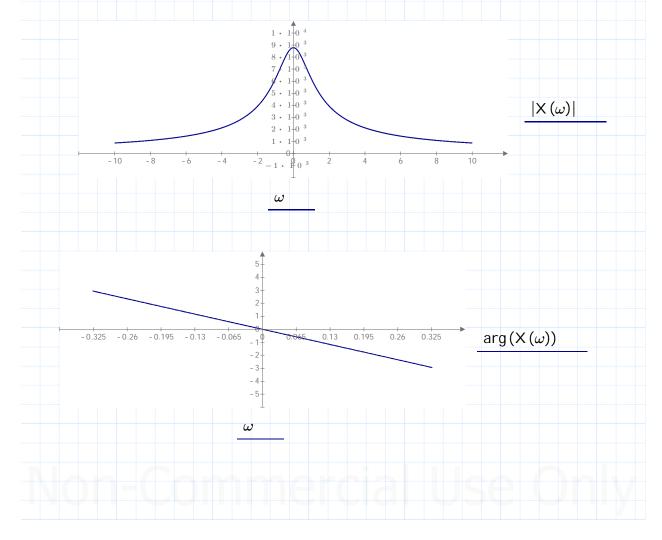
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$$j := \sqrt{-1} \qquad \omega := -10 \cdot \pi, -9.999 \cdot \pi .. 10 \cdot \pi \qquad X(\omega) := 0 \qquad \text{initialise } X(w)$$
$$X(\omega) := \left(\frac{1}{\sqrt{2 \cdot \pi}}\right) \int_{-10}^{10} x_{\exp}(t) \cdot u(t) \cdot e^{-j \cdot \omega \cdot t} dt \qquad \text{The Fourier Transform Formula}$$

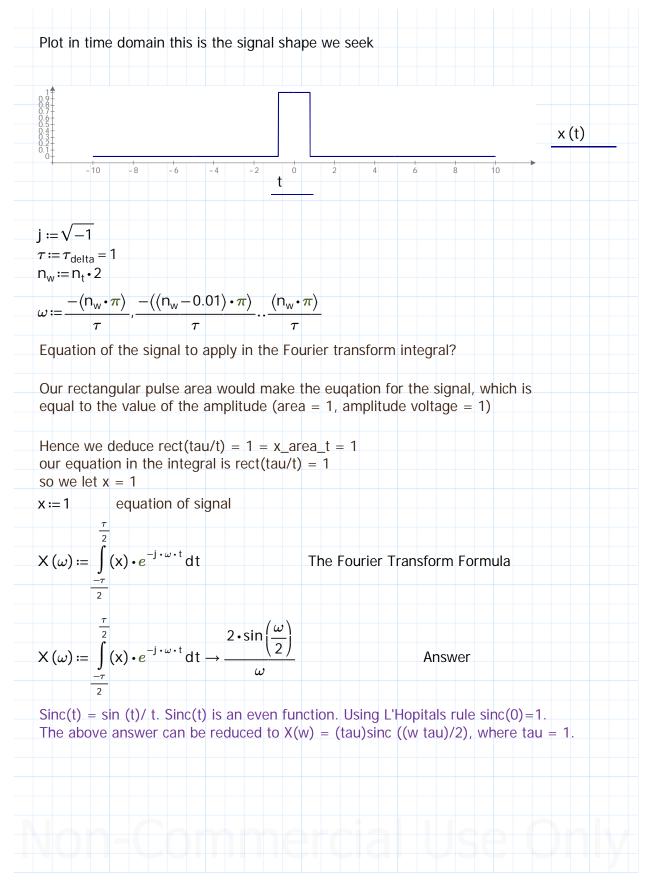
To calculate the integral set a = 1 or -1, the limits from 0 to 10 since there it it NOT equal to 0 here.

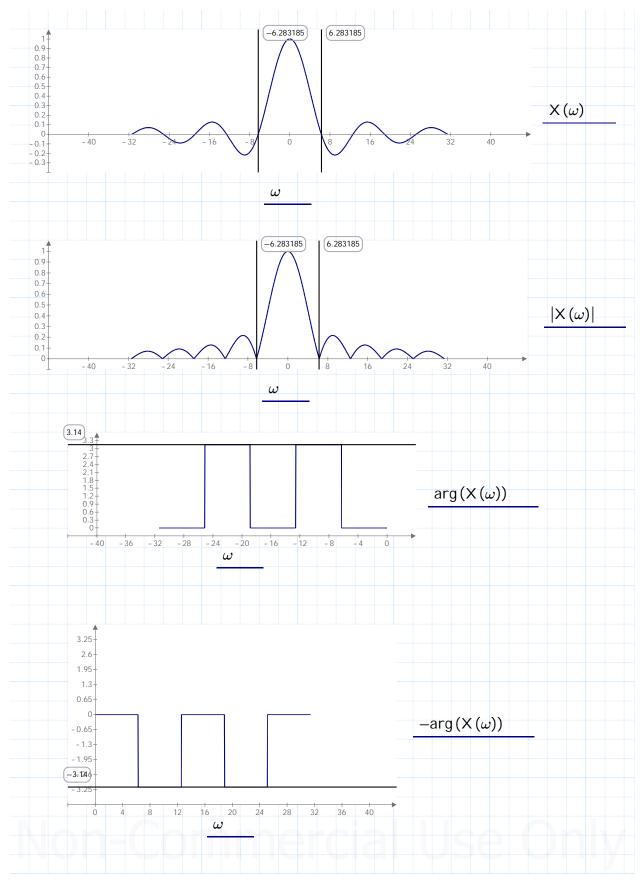
$$X(\omega) \coloneqq \left(\frac{1}{\sqrt{2 \cdot \pi}}\right) \int_{-0}^{10} (x_{\exp}(t) \cdot u(t)) \cdot e^{-j \cdot \omega \cdot t} dt \rightarrow \frac{\sqrt{2} \cdot (e^{10} \cdot e^{-(10i \cdot \omega)} - 1) \cdot (1 + \omega \cdot 1i)}{2 \cdot \sqrt{\pi} \cdot (\omega^2 + 1)}$$

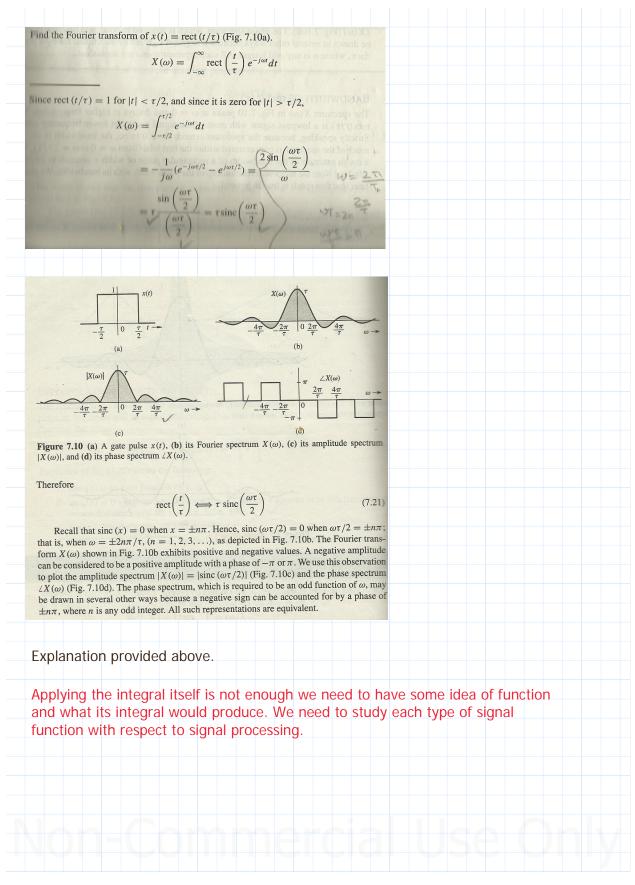
The above integral result is not the textbook example answer, because its a theorectical example. However the calculated integral shows Prime can perform the calculation, the magnitude plot is close to the theorectical result in terms of the shape of the plot, the amplitude is high. Similarly phase angle plot is slightly different.



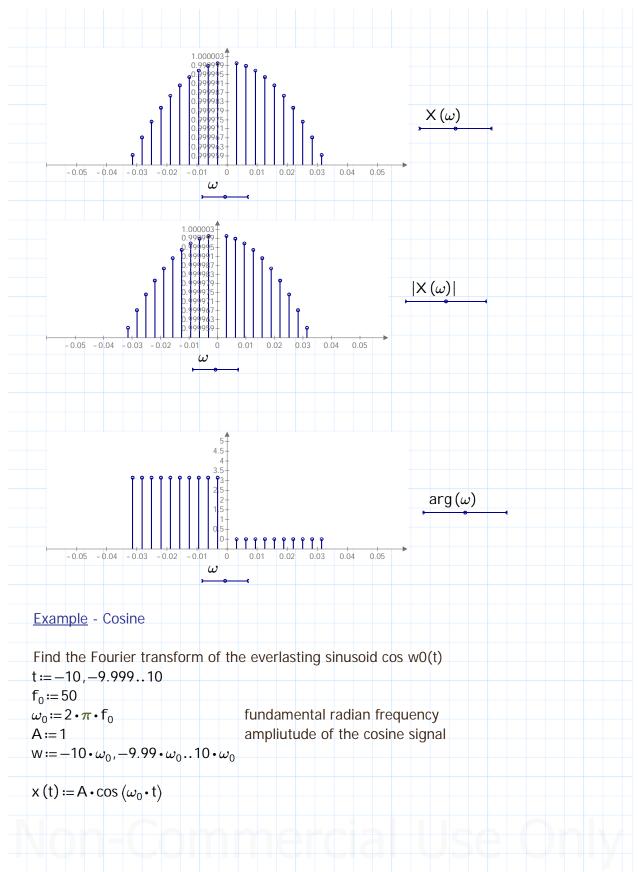
clear(x)	$\operatorname{clear}\left(\omega ight)$	clear(t)	clear (n)	
0.5		Hatched area is e <b>T</b> is set to 1 So the equation r hatched area is		Sketch example for meeting the objective of the example problem.
	- <u>T</u> 2	י <u>ר</u> 2		
			of unit value ho	
			prizontal and ver	tical axis is pi 3.142
$\tau_{\rm Lin} := \frac{\left(\frac{\Pi_{\tau}}{\Pi_{\tau}}\right)}{\left(\frac{\Pi_{\tau}}{\Pi_{\tau}}\right)}$	$\frac{\cdot(\pi)}{2} - \frac{(-n_{\tau} \cdot \pi)}{2}$		time domain	signal width - tau axis horizonta
$ au_{\text{delta}} = 1$	pu <sub>scale</sub>	tau along	<b>U</b> 1 1	(t)) is expanded by a factor axis, and therefore can be
AmpV <sub>vrt</sub> ≔	n <sub>τ</sub> amplit nt (nta	ude value - vei		voltage with a value equal to
$\mathbf{x}_{area_t} \coloneqq \langle \tau_d$	<sub>elta</sub> •AmpV <sub>vrt</sub> )	time domair value at hor		amplitude equal to tau
$x_{area_t} = 1$	pulse area			
now set the	e value of tau w	ith respect to t	he plot of the sig	gnal above
$\tau \coloneqq \frac{n_{\tau} \cdot (\boldsymbol{\pi})}{2}$				
n <sub>t</sub> :=5	time range - ho	prizontal axis		
t ≔ —10, —9	.9910			
$\mathbf{x}(t) \coloneqq \mathbf{if}( t )$	$\left  < \frac{\tau}{2}, \mathbf{x}_{area_t}, 0 \right\rangle$	defining the	function equal t	o x_area_t when  t  <tau 2,="" else<="" td=""></tau>
Now we wil axis) and V but signals	l focus just on t = 1 (vertical ax	he one rectang kis). Just the or user needs, and	gular pulse with a ne rectangular pu d the objective is	a width of tau (horizontal ulse. This attempt is amateur s to apply Fourier transforms

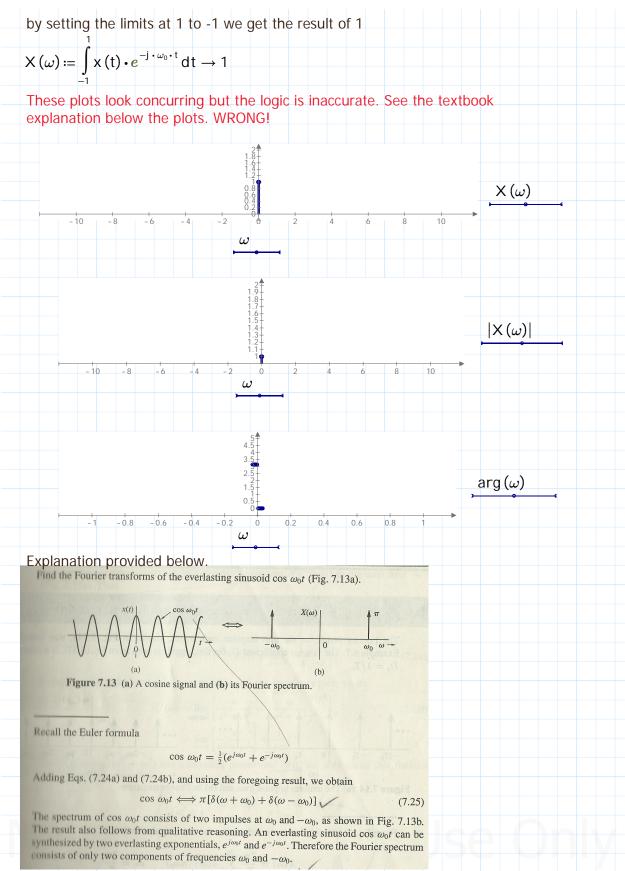






x(t) := if(t = 0, 1, 0)	unit impulse fur	nction
t ≔ −10, −9.99910	impulse of value	to be made small here it is 0.001 then the e 1 is seen as a straight line at time $t = 0$ , ngle shape is seen at $t=0$
-10 -8 -6	1 0.9 0.8 0.7 0.6 0.5 0.4 0.3 0.2 0.1 4 -2 Q 2 4 2 4	<u>x (t)</u>
	+	
		the Fourier transform equation.
	cannot be placed in t=0, elsewhere it is n is x(t=0) = 1, whic rm of the unit impuls This is Prime delta delta(m,n) m=t tim value of 1. This fur a 1 in the integral	<ul> <li>0. So the equation that best</li> <li>ch is really x=1.</li> <li>se function = 1</li> <li>function for unit impulse</li> <li>ne, when t= 0 t=n, and the function returns the</li> <li>nction will not work in the integral either. Placing is not accurate because that the output of the</li> </ul>
The signal is 1 at time represents the function So the Fourier transfort $t := 0$ $\delta(t, 0) = 1$	cannot be placed in t=0, elsewhere it is n is x(t=0) = 1, whic rm of the unit impuls This is Prime delta delta(m,n) m=t tin value of 1. This fur a 1 in the integral function not the fu	<ul> <li>0. So the equation that best</li> <li>ch is really x=1.</li> <li>se function = 1</li> <li>function for unit impulse</li> <li>ne, when t= 0 t=n, and the function returns the</li> <li>nction will not work in the integral either. Placin</li> <li>is not accurate because thats the output of the</li> </ul>
The signal is 1 at time represents the function So the Fourier transfo	cannot be placed in t=0, elsewhere it is n is $x(t=0) = 1$ , whic rm of the unit impuls This is Prime delta delta(m,n) m=t tim value of 1. This fur a 1 in the integral function not the fu $\pi$ 0.01. $\pi$ The Fourie t We place the upper would res	<ul> <li>0. So the equation that best</li> <li>ch is really x=1.</li> <li>se function = 1</li> <li>function for unit impulse</li> <li>ne, when t= 0 t=n, and the function returns the</li> <li>nction will not work in the integral either. Placing is not accurate because that the output of the</li> </ul>





Chapter 3 Frequency Domain Analysis - Fourier Transform (FT), Inverse Fourier Transform and FT Spectra Entered by: Karl S Bogha Dhaliwal - Grad Cert Power Systems Protection and Relaying Uni of Idaho. USA. BSE - Arkansas State U 1990. BSc - USAO Oklahoma 1986.

Operation	x(t)	$X(\omega)$
Scalar multiplication	kx(t)	$kX(\omega)$
Addition	$x_1(t) + x_2(t)$	$X_1(\omega) + X_2(\omega)$
Conjugation	$x^*(t)$	$X^*(-\omega)$
Duality	X(t)	$2\pi x(-\omega)$
Scaling (a real)	x(at)	$\frac{1}{ a }X\left(\frac{\omega}{a}\right)$
Time shifting	$x(t-t_0)$	$X(\omega)e^{-j\omega t_0}$
Frequency shifting ( $\omega_0$ real)	$x(t)e^{j\omega_0 t}$	$X(\omega-\omega_0)$
Time convolution	$x_1(t) * x_2(t)$	$X_1(\omega)X_2(\omega)$
Frequency convolution	$x_1(t)x_2(t)$	$\frac{1}{2\pi}X_1(\omega)*X_2(\omega)$
Time differentiation	$\frac{d^n x}{dt^n}$	$(j\omega)^n X(\omega)$
Time integration	$\int_{-\infty}^t x(u)du$	$\frac{X(\omega)}{j\omega} + \pi X(0)\delta(\omega)$

Here the focus is on signal processing so we are concerned with signals that are of use in applications, not solving problems in mathematics in general.

So the function to be Fourier transformed needs to have signal characteristics or properties for application and or processing in systems.

Inverse Fourier Transform

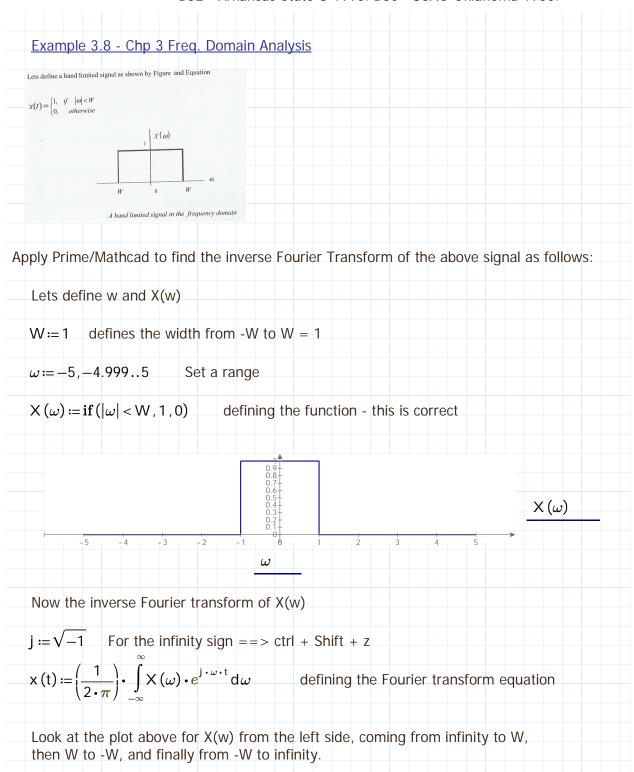
In our use of Fourier Transforms we want the result to be represented with respect to the radian frequency w. This is what we see in the horizontal axis. Frequency Domain.

Given the Fourier Transform of a signal (wrt to w) we want to find the original signal with respect to time.

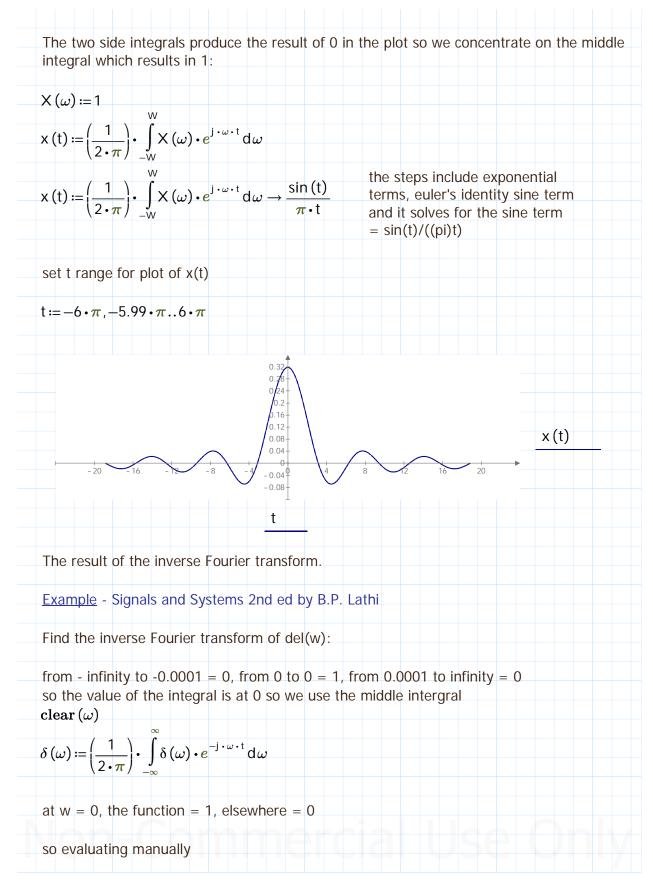
Time Domain.

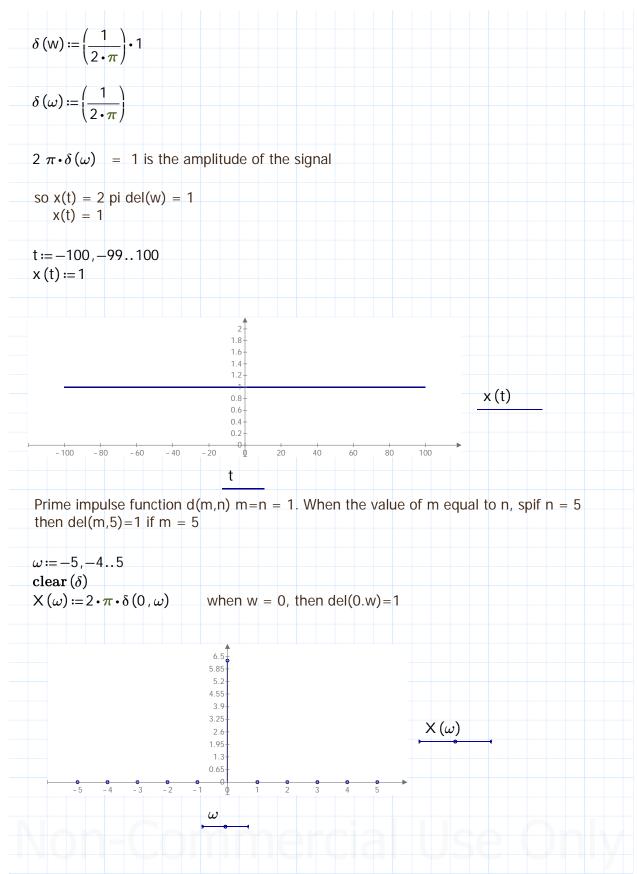
 $x(t) = \frac{1}{2\pi} \int_{T}^{2} X(\omega) e^{j\omega t} d\omega$ 

<--- Equation for the Inverse Fourier Transform



$$\mathbf{x}(\mathbf{t}) \coloneqq \left(\frac{1}{2 \cdot \pi}\right) \cdot \int_{-\infty}^{-W} \mathbf{X}(\omega) \cdot e^{\mathbf{j} \cdot \omega \cdot \mathbf{t}} \, \mathrm{d}\omega + \left(\frac{1}{2 \cdot \pi}\right) \cdot \int_{-W}^{W} \mathbf{X}(\omega) \cdot e^{\mathbf{j} \cdot \omega \cdot \mathbf{t}} \, \mathrm{d}\omega + \left(\frac{1}{2 \cdot \pi}\right) \cdot \int_{W}^{\infty} \mathbf{X}(\omega) \cdot e^{\mathbf{j} \cdot \omega \cdot \mathbf{t}} \, \mathrm{d}\omega$$





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### Fourier Transform Spectra

Notes from Signals and Systems 2nd ed BP Lathi Publisher Oxford

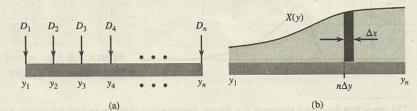
## 7.1-1 Physical Appreciation of the Fourier Transform

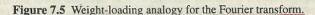
In understanding any aspect of the Fourier transform, we should remember that Fourier representation is a way of expressing a signal in terms of everlasting sinusoids (or exponentials). The Fourier spectrum of a signal indicates the relative amplitudes and phases of sinusoids that are required to synthesize that signal. A periodic signal Fourier spectrum has finite amplitudes and exists at discrete frequencies ( $\omega_0$  and its multiples). Such a spectrum is easy to visualize, but the spectrum of an aperiodic signal is not easy to visualize because it has a continuous spectrum. The continuous spectrum concept can be appreciated by considering an analogous, more tangible phenomenon. One familiar example of a continuous distribution is the loading of a beam. Consider a beam loaded with weights  $D_1, D_2, D_3, \ldots, D_n$  units at the uniformly spaced points  $y_1, y_2, \ldots, y_n$ , as shown in Fig. 7.5a. The total load  $W_T$  on the beam is given by the sum of these loads at each of the *n* points:

$$W_T = \sum_{i=1}^n D_i$$

Consider now the case of a continuously loaded beam, as depicted in Fig. 7.5b. In this case, although there appears to be a load at every point, the load at any one point is zero. This does not mean that there is no load on the beam. A meaningful measure of load in this situation is not the load at a point, but rather the loading density per unit length at that point. Let X(y) be the loading density per unit length of beam. It then follows that the load over a beam length  $\Delta y(\Delta y \rightarrow 0)$ , at some point y, is  $X(y)\Delta y$ . To find the total load on the beam, we divide the beam into segments of interval  $\Delta y(\Delta y \rightarrow 0)$ . The load over the *n*th such segment of length  $\Delta y$  is  $X(n\Delta y)\Delta y$ . The total load  $W_T$  is given by

$$W_T = \lim_{\Delta y \to 0} \sum_{y_1}^{y_n} X(n \Delta y) \Delta y$$
$$= \int_{y_1}^{y_n} X(y) \, dy$$





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# CHAPTER 7 CONTINUOUS-TIME SIGNAL ANALYSIS: THE FOURIER TRANSFORM

The load now exists at every point, and y is now a continuous variable. In the case of discrete loading (Fig. 7.5a), the load exists only at the *n* discrete points. At other points there is no load. On the other hand, in the continuously loaded case, the load exists at every point, but at any specific point y, the load is zero. The load over a small interval  $\Delta y$ , however, is  $[X(n\Delta y)] \Delta y$  (Fig. 7.5b). Thus, even though the load at a point y is zero, the relative load at that point is X(y).

An exactly analogous situation exists in the case of a signal spectrum. When x(t) is periodic, the spectrum is discrete, and x(t) can be expressed as a sum of discrete exponentials with finite amplitudes:

$$x(t) = \sum_{n} D_n e^{jn\omega_0}$$

For an aperiodic signal, the spectrum becomes continuous; that is, the spectrum exists for every value of  $\omega$ , but the amplitude of each component in the spectrum is zero. The meaningful measure here is not the amplitude of a component of some frequency but the spectral density per unit bandwidth. From Eq. (7.6b) it is clear that x(t) is synthesized by adding exponentials of the form  $e^{jn\Delta\omega t}$ , in which the contribution by any one exponential component is zero. But the contribution by exponentials in an infinitesimal band  $\Delta\omega$  located at  $\omega = n\Delta\omega$  is  $(1/2\pi)X(n\Delta\omega)\Delta\omega$ , and the addition of all these components yields x(t) in the integral form:

$$x(t) = \lim_{\Delta\omega\to 0} \frac{1}{2\pi} \sum_{n=-\infty}^{\infty} X(n\Delta\omega) e^{(jn\Delta\omega)t} \Delta\omega = \frac{1}{2\pi} \int_{-\infty}^{\infty} X(\omega) e^{j\omega t} d\omega$$
(7.17)

Thus,  $n\Delta\omega$  approaches a continuous variable  $\omega$ . The spectrum now exists at every  $\omega$ . The contribution by components within a band  $d\omega$  is  $(1/2\pi)X(\omega) d\omega = X(\omega) df$ , where df is the bandwidth in hertz. Clearly,  $X(\omega)$  is the spectral density per unit bandwidth (in hertz).<sup>†</sup> It also follows that even if the amplitude of any one component is infinitesimal, the relative amount of a component of frequency  $\omega$  is  $X(\omega)$ . Although  $X(\omega)$  is a spectral density, in practice it is customarily called the *spectrum* of x(t) rather than the spectral density of x(t). Deferring to this convention, we shall call  $X(\omega)$  the Fourier spectrum (or Fourier transform) of x(t).

<sup>†</sup>To stress that the signal spectrum is a *density* function, we shall shade the plot of  $|X(\omega)|$  (as in Fig. 7.4b). The representation of  $\angle X(\omega)$ , however, will be a by a line plot, primarily to avoid visual confusion.

## Example - With its understanding (Stem Plots)

We can use the knowledge we gained from the previous section to perform spectral analysis in Mathcad.

Let the frequency of a signal be x(t) be

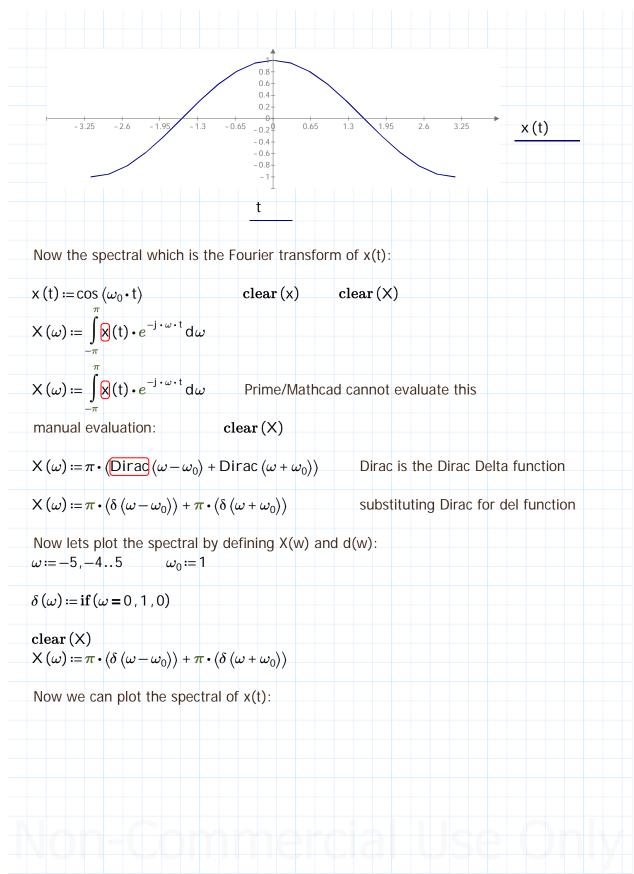
 $\omega_0 \coloneqq 1$ 

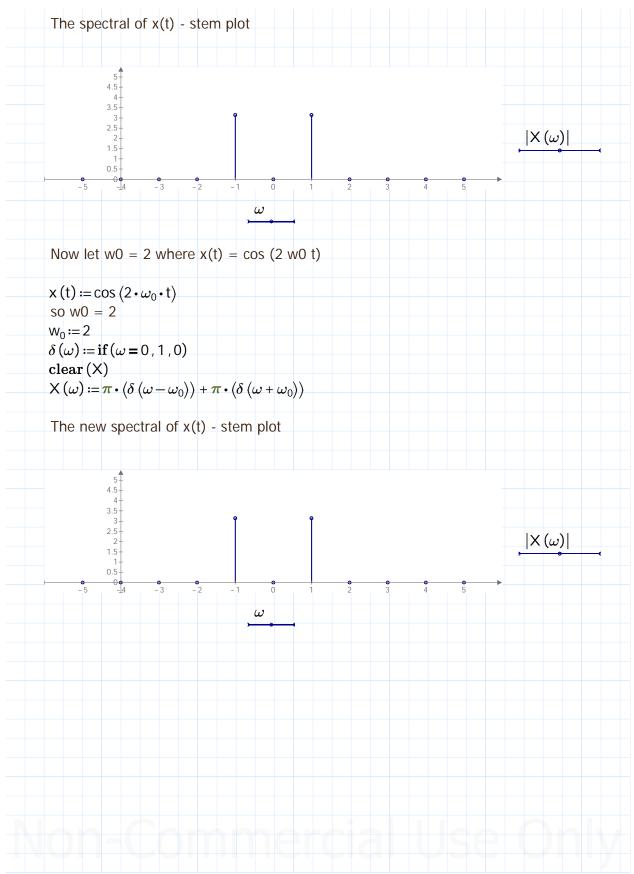
 $\mathbf{x}(\mathbf{t}) \coloneqq \cos(\omega_0 \cdot \mathbf{t})$ 

 $t \coloneqq -\pi, -0.9 \cdot \pi \dots \pi$ 

Plot of x(t):

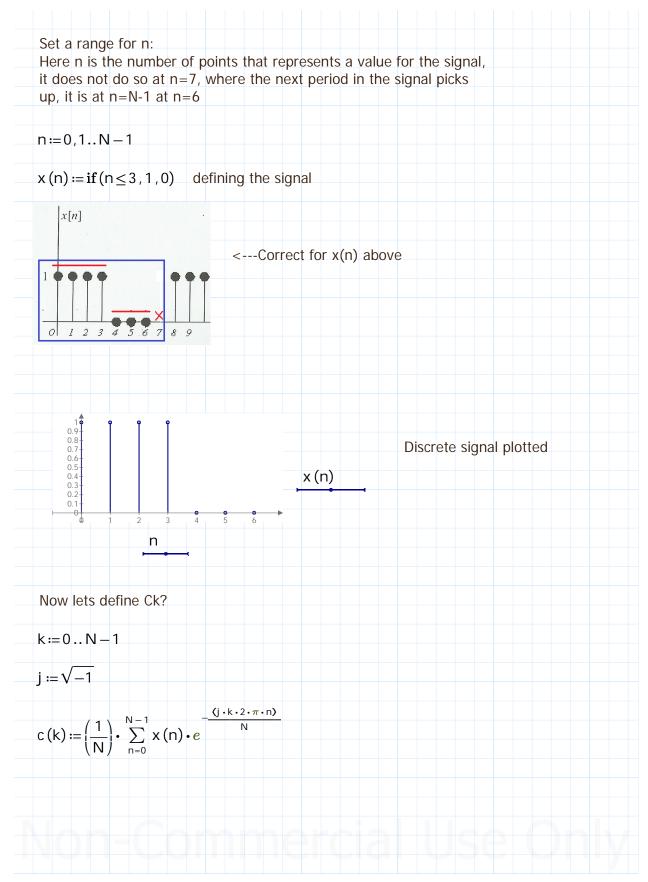
Page 38 of 52

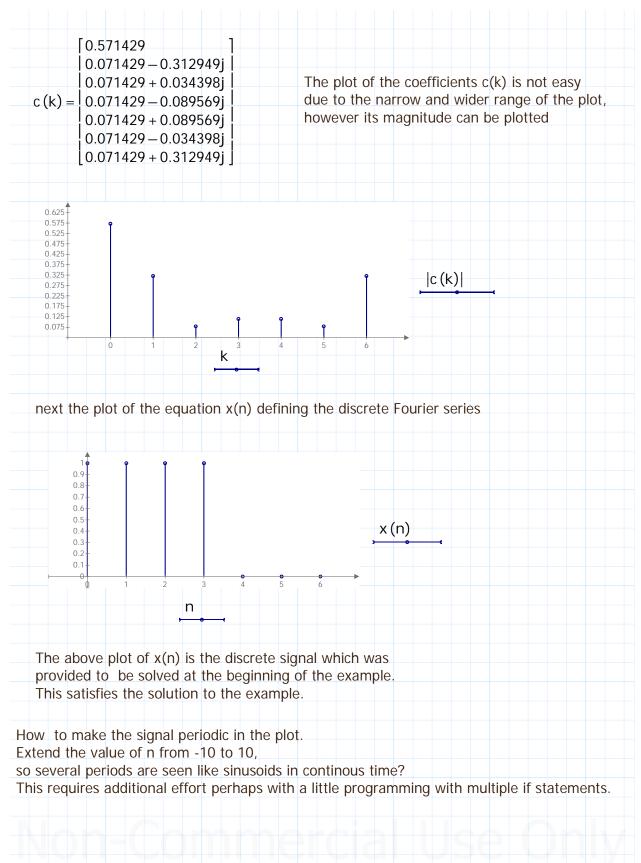




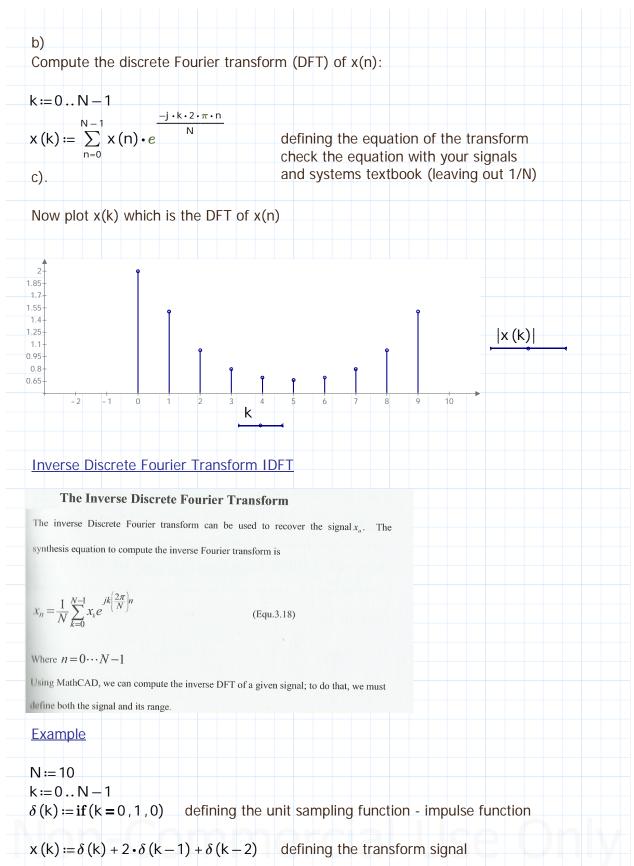
Signals and Systems Using Mathcad (Tutorial) by Derose and Veronis. Chapter 3 Frequency Domain Analysis - Fourier Transform (FT), Inverse Fourier Transform and FT Spectra Entered by: Karl S Bogha Dhaliwal - Grad Cert Power Systems Protection and Relaying Uni of Idaho. USA. BSE - Arkansas State II 1990 BSc - USAO Oklahoma 1986

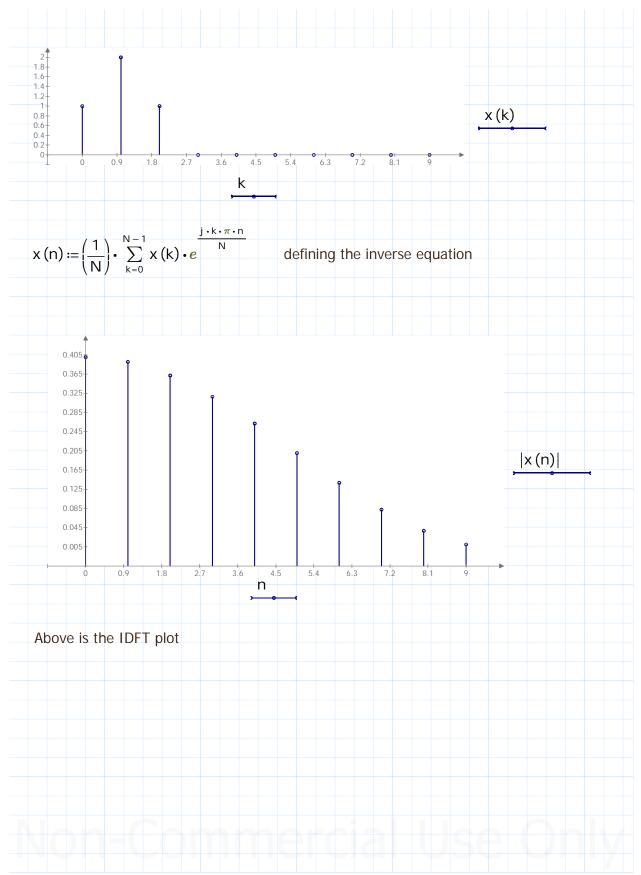
Discre	te Time Fourier Series:
	r examples the focus was on continous time signals, now the focus is on discrete ignals.
of sine	ve used Fourier series to approximate a continous time periodic signal as a sum e and cosine. By replacing sine and cosine with Euler's identity, the series es to exponential Fourier series.
discre	screte time signals we can use a similar approach to approximate te time periodic signals. In this example we learn more about discrete fourier series and how to use Mathcad to manage it.
x(n) =	rete periodic signal = x(n + N)
can be	e approximated by using the discrete-time Fourier series equation.
$x(n) = \sum_{k=1}^{N-1} \sum_{k=1}$	$\int_{0}^{1} c_{k} e^{\frac{jk2\pi n}{N}} \qquad \text{where} \qquad c_{k} = \frac{1}{N} \sum_{k=0}^{N-1} x(n) e^{\frac{-jk2\pi n}{N}}$
and $n=0$	··· <i>N</i> -1
	<u>ole - Discrete Time Fourier Series</u> te time periodic signal shown below
x[n]	
0 1	2 3 4 5 6 7 8 9
Objec	tive is to find an equation that represents this signal, x(n)?
Fist fi	nd the period of the signal?
From	ing the signal just like a sunusoid signal, the period is 7. 0 to $3 = 1$ , then drops to 0 from 4 to 6, and there is space before 7 so the ends at 7, and picks back up again with a new period at 7
Instea	Id of T, here in the discrete form we use N
N ≔ 7	discrete period





The Discrete Fourier T	ransform	
	egral to approximate a single pulse in continuous	
	h N sample, we can use the Discrete Fourier	
Transform to approximate the signal.	Let $x_n$ be some sample of a signal, the Discrete	
Fourier Transform (DFT) of $x_n$ can be e	valuated by using Equ	
$x_k = \frac{1}{N} \sum_{k=0}^{N-1} x_n e^{-jk \left(\frac{2\pi}{N}\right)n}$		
$A_k = \overline{N} \sum_{k=0}^{\infty} A_n e^{-k}$		
	athcad) to compute the DFTs of xn from the	
following steps.		
a).		
	et the subscript of the array to negative. an index arrays from both positive and negative.	
clear (n)	an index arrays from both positive and negative.	
• •	we can enable negative tracking	
-		
N := 10		
$N \coloneqq 10$ $j \coloneqq \sqrt{-1}$		
N := 10		
N := 10 $j := \sqrt{-1}$ n := 0 N - 1		
N := 10 $j := \sqrt{-1}$ n := 0 N - 1 $u(n) := if(n \ge 0, 1, 0)$		
N := 10 $j := \sqrt{-1}$ n := 0 N - 1 $u(n) := if(n \ge 0, 1, 0)$		
N := 10 $j := \sqrt{-1}$ n := 0 N - 1 $u(n) := if(n \ge 0, 1, 0)$	defining the step function	
$N := 10$ $j := \sqrt{-1}$ $n := 0 \dots N - 1$ $u(n) := if(n \ge 0, 1, 0)$ $x(n) := \left(\frac{1}{2}\right)^{n} \cdot u(n)$	defining the step function	
N := 10 j := √-1 n := 0 N - 1 u (n) := if (n ≥ 0, 1, 0) x (n) := $\left(\frac{1}{2}\right)^{n} \cdot u(n)$	defining the step function	
$N := 10$ $j := \sqrt{-1}$ $n := 0 \dots N - 1$ $u(n) := if(n \ge 0, 1, 0)$ $x(n) := \left(\frac{1}{2}\right)^{n} \cdot u(n)$	defining the step function	
N := 10 j := √-1 n := 0 N - 1 u (n) := if (n ≥ 0, 1, 0) x (n) := $\left(\frac{1}{2}\right)^{n} \cdot u(n)$	defining the step function	
N := 10 j := √-1 n := 0 N - 1 u (n) := if (n ≥ 0, 1, 0) x (n) := $\left(\frac{1}{2}\right)^n \cdot u(n)$	defining the step function	
N := 10 j := √-1 n := 0 N - 1 u (n) := if (n ≥ 0, 1, 0) x (n) := $\left(\frac{1}{2}\right)^n \cdot u(n)$	defining the step function defining the signal	
N := 10 j := √-1 n := 0 N - 1 u (n) := if (n ≥ 0, 1, 0) x (n) := $\left(\frac{1}{2}\right)^n \cdot u(n)$	defining the step function	
$N := 10$ $j := \sqrt{-1}$ $n := 0 N - 1$ $u(n) := if(n \ge 0, 1, 0)$ $x(n) := \left(\frac{1}{2}\right)^{n} \cdot u(n)$ $u(n) := \left(\frac{1}{2}\right)^{n} \cdot u(n)$	defining the step function defining the signal	
$N := 10$ $j := \sqrt{-1}$ $n := 0 N - 1$ $u(n) := if(n \ge 0, 1, 0)$ $x(n) := \left(\frac{1}{2}\right)^{n} \cdot u(n)$ $u(n) := \left(\frac{1}{2}\right)^{n} \cdot u(n)$	defining the step function defining the signal	
N := 10 j := √-1 n := 0 N - 1 u (n) := if (n ≥ 0, 1, 0) x (n) := $\left(\frac{1}{2}\right)^n \cdot u(n)$	defining the step function defining the signal	
$N := 10$ $j := \sqrt{-1}$ $n := 0 N - 1$ $u(n) := if(n \ge 0, 1, 0)$ $x(n) := \left(\frac{1}{2}\right)^{n} \cdot u(n)$ $u(n) := \left(\frac{1}{2}\right)^{n} \cdot u(n)$	defining the step function defining the signal	





Discrete Ti	me Fourier Trans	<u>form</u>					
The Dis	crete Time Fourier	Transform					
The Discrete Ti	ne Fourier Transform (DT	FT) can be used	to compute the	Fourier			
transform of an	nfinite length discrete time	signal. The assump	ption is that the	result of			
the summation of	f the infinite length must b	e converged. In c	other words, th	e infinite			
length sequence	x(n) must be absolutely sur	nmable, where $\sum_{n=-\infty}^{\infty}$	$x(n)   < \infty$ . The	Discrete			
Time Fourier Tr	ansform of a given signal	x(n) is denoted 1	by $X(e^{j\omega})$ and	d can be			
calculated from I	qu. In this section we	show how to use M	1athCAD to cor	npute the			
Discrete Time F	ourier Transform of a given	signal, both graph	ically and sym	bolically.			
Later, we will als	o show you how to compute	the synthesis version	on of the DTFT,	which is			
the inverse Disc	ete Time Fourier Transforr	n of the sequence.	The equation	below is			
used to compute	he DTFT of a given signal x	( <i>n</i> ).					
	$X(e^{j\omega}) = \sum_{n=-\infty}^{\infty} x(n)e^{-j\omega}$	on Equ					
	n=						
Example 3	20						
j ≔√_1							
$u(n) \coloneqq \Phi(n)$	ı) Prime buil	t-in step fur	nction				
1							
$a \coloneqq \frac{1}{2}$							
$x(n) := a^{n}$	u(n) This is	the signal v	we need t	o find its	DTFT		
, (, , , , , , , , , , , , , , , , , ,		the eighter i					
$X(\omega) \coloneqq \sum_{n=0}^{\infty}$	$x(n) \cdot e^{-j \cdot \omega \cdot n}$	Defining t	he DTFT (	equation			
Continuing	with the require	ments for a	final plot:				
u(n) := if(I)	1 = 0, 1, 0						
$a \coloneqq \frac{1}{2}$							
$x(n) := a^n$	u (n)						

