# Putting Engineering First and Mathematics Second in Engineering Education


## Ifiok Otung

### University of Glamorgan


### August 2002

# CONTENTS

# Introduction

The worrying decline in mathematics skills and appetite amongst University entrants in the UK has been well reported [1-2]. Many students perceive mathematics as a difficult subject. The 29% failure rate recorded in AS-level mathematics in 2001, compared to a much lower average failure rate of 13% in other AS subjects [3], will have served to strengthen this unfortunate image of maths.

Urgent Government action is required in pre-19 mathematics education to

- Boost the supply of qualified maths teachers
- Improve the image of mathematics amongst young people
- Significantly increase the fraction of sixth-formers taking A-level maths, currently standing at about 9% [4], and
- Raise the essential maths skills of the end products.

This is a long-term solution that may take years of concerted effort to yield tangible improvements. In the mean time however, engineering educators must consider ways of softening the impact of the above maths problem on the study of engineering. In the current maths climate, numbers recruited to engineering programmes from a largely *mathophobic* pool will dwindle if the perception remains that engineering is a highly mathematical and hence difficult subject.

Secondly, high withdrawal rates of first-year students — up to 29% in one UK engineering department [2] — will continue to be a big problem if mathematically-deficient recruits are introduced to engineering using a level of maths for which they are ill-prepared. Diagnostic testing and individually tailored follow-up remedial measures are now widely used in engineering departments. But if confronted with a lot of maths content in engineering courses during the crucial early period, some of the target students may become discouraged and contemplate a premature exit before the deficiencies in their maths attitude and skills have been remedied.

In this report, I invite you as an engineering academic or other interested party to critically examine the case for adapting and modernising our engineering teaching approach in the 21st century. In order to juxtapose two teaching approaches: *engineering-first* and *maths-first*, the report includes an introductory lecture on the topic of signal sampling, which features prominently in communication engineering and digital signal processing. You do not need to be familiar with this topic in order to understand the material discussed. In fact it is preferable if you are completely new to sampling. For lack of space the topic is not treated in exhaustive detail, but enough of the same ground is covered using either approach to allow you to assess the relative merits of the two approaches. The conclusion provides my assessment of the two approaches based on my own experience with engineering students and practising engineers.

# The Case For Putting Engineering First

Writing last year in the Engineering Science and Education Journal (ESEJ) [2,5] I argued that engineering education would benefit from a new introductory teaching approach that puts engineering first and removes what many potential recruits perceive as an unfriendly maths gatekeeper. I suggested an introductory approach that subordinates mathematical rigour to an excellent insight into the engineering concept at hand and a thorough understanding of the interplay of relevant design parameters. Advances in ICT have made a revolutionary impact on the way engineers work in the 21st century. It is high time engineering academics took cognisance of these positive developments and adapted and modernised their teaching approach. Today's engineer is no longer limited to pen, paper, slide rule and mathematical/statistical tables for their calculations, but can obtain reliable solutions of mathematical problems using ubiquitous software packages.

Kent [6] examined the maths involved in the work of engineers in a large multidisciplinary engineering consulting firm in the UK and found that analytical work is done largely by computer software and only 2% of the engineers in the company were analytical specialists able to deal with any non-standard or ambiguous problems.

I should emphasise for the avoidance of misconstruction that I am not recommending a non-mathematical engineering content. As established in my ESEJ article, maths is indispensable to engineering. A number of analogies are useful in stressing this point:

- Maths is like an insurance policy: it's better to have it and not need it than to need it and not have it.
- Maths is like a foreign language: it never hurts to understand it even if you don't use it.
- Maths is like a diving board experience: the longer you wait the harder it gets.
- Maths and engineering are in something like a parent/child relationship: maths may not need engineering but engineering needs maths.

However, one must question the wisdom of scaring away potentially successful engineers with a mathematical content that is rarely used during the career of ~98% of practitioners. A more productive approach for engineering training in the 21st century would be to introduce each engineering topic using such means as lucid graphs and diagrams, intuitive reasoning, analogies, computer simulations, etc. to give the student an unclouded insight into the engineering concept and the underlying physical considerations, a clear appreciation of the parameters involved, and a good feel for the interplay of these parameters. This type of first-encounter with the subject would not only stimulate the student's interest but it would crucially erect knowledge pegs on which they can hang a more precise subsequent discourse involving the language of mathematics. A firm foundation thus laid, the student can handle and in some cases even enjoy a more mathematically rigorous approach during later encounters with the topic when any deficiencies in maths skills will have been remedied.

This approach puts engineering first and maths second, and better equips the student with the insight and technical competence that will contribute to a successful engineering career. It should be contrasted with the following reverse approach, which is still in widespread use: maths comes first and an elegant mathematical derivation of an engineering concept is presented to students many of whom do not yet possess the skills or motivation to follow. The end result is students who are sadly lacking in confidence and a clear insight into the problem. These students often skip the abstruse derivation steps and jump to the final ‘black-box’ formula. They are effectively in the same boat as those who receive the same magic formula prefaced with the well-worn ‘it-can-be-shown’ phrase.

To illustrate, consider an introductory lecture dealing with the topic of sampling in the field of communication engineering. We will discuss this topic using an engineering-first approach followed by a maths-first approach before drawing conclusions on the relative merits of each approach.

# Engineering-First Introduction To Sampling

An analogue signal $g(t)$ is continuous in time and value, and requires exclusive use of a communication system resource for the entire duration of transmission. It is of interest to consider whether $g(t)$ can be faithfully reconstructed at the receiving end from values of $g(t)$ taken at intervals $T_s > 0$. This *sampling* process converts the *continuous-value continuous-time* signal $g(t)$ to a continuous-value *discrete-time* signal (or sequence) $g(nT_s)$, where $n = 0, 1, 2, 3, \ldots$; $T_s$ is the *sampling interval*, and its reciprocal $f_s = 1/T_s$ is known as the *sampling frequency* or *sampling rate* in hertz (Hz). The benefits of transmitting $g(nT_s)$ rather than $g(t)$ are enormous:

- The communication system resource can be allocated to other user signals during the unused intervals, thus providing communication services to more people at the same time, reducing the cost of communication to each user, and maximising profit for the communication service provider.
- Going one step further, we can constrain $g(nT_s)$ to a finite set of possible values, a process known as *quantisation*, which we will not discuss any further here. The sequence of values can be digitally encoded before transmission, thus exploiting the numerous advantages of digital communication.

The surprise is that the original information signal $g(t)$ can be perfectly reconstructed from the sampled signal $g(nT_s)$ provided $T_s$ satisfies a simple rule contained in the *sampling theorem*. To see the rule governing the selection of $T_s$ and how the reconstruction of $g(t)$ from $g(nT_s)$ is achieved, consider first a sinusoidal signal.

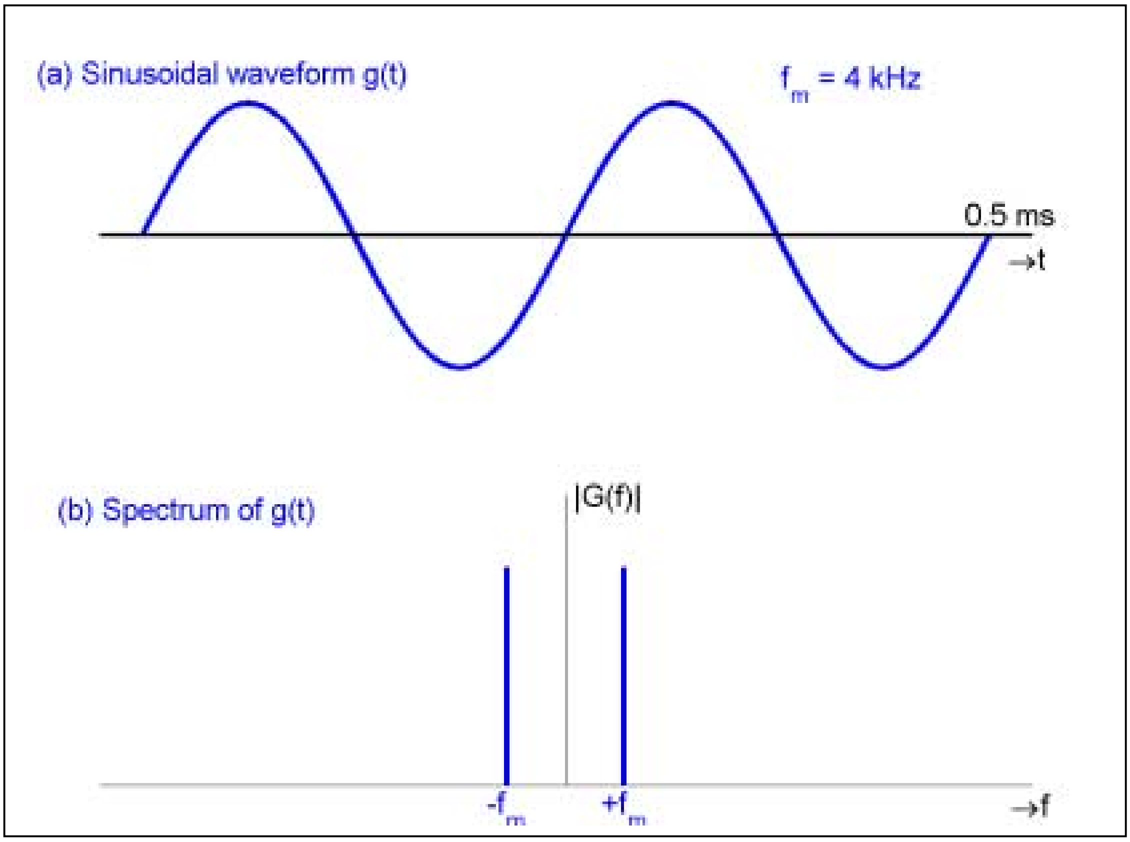


**Figure 1: Waveform and spectrum of analogue signal**

Figure 1a shows a 0.5ms segment of a sinusoidal signal $g(t)$. This waveform represents a unique frequency $f_m$ (= 4kHz in this example). That is, no other frequency will fit $g(t)$. The amplitude spectrum of $g(t)$, denoted $|G(f)|$ and showing the amplitude of each sinusoidal component of $g(t)$, therefore consists of a single line of height $A$ at frequency $f = f_m$. This is a single-sided spectrum. The preferred double-sided spectral representation of $g(t)$ shown in Figure 1b simply exploits the identity

$$A\cos(2\pi f_m t) \equiv \tfrac{A}{2}\cos(2\pi f_m t) + \tfrac{A}{2}\cos[2\pi(-f_m)t]$$

and shares the amplitude equally between the frequency pair $\pm f_m$.

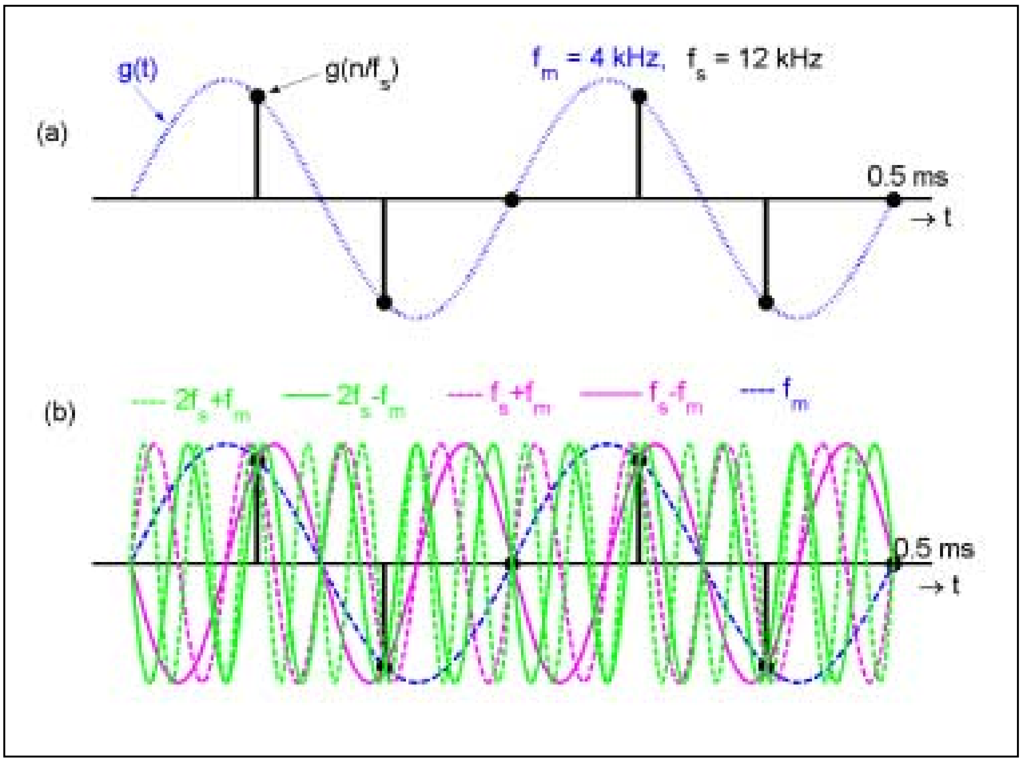


**Figure 2: Samples of $f_m$ at rate $f_s$ contain frequencies $jf_s \pm f_m$, $j$=0, 1, 2, 3, ...**

Sampling the sinusoid $g(t)$ at a rate $f_s$ (= 12 kHz in this example) yields the sequence $g(nT_s) \equiv g(n/f_s)$ shown in Figure 2a. Note however that, unlike $g(t)$, the sampled signal $g(nT_s)$ no longer represents a unique frequency; rather it fits (i.e. contains) an infinite set of frequencies, $f_m$, $f_s - f_m$, $f_s + f_m$, $2f_s - f_m$, $2f_s + f_m$, ..., $jf_s \pm f_m$, ..., as shown in Figure 2b up to $j$ = 2. The frequencies $jf_s \pm f_m$ for $j \geq 1$ are known as *image frequencies*, while $f_m$ is referred to as the *baseband frequency*. In Figure 3a it is further shown that the sum of the baseband and image sinusoids yields $g(nT_s)$, where we have included image frequencies up to $j = 10$. The fit becomes exact as $j \to \infty$. Thus the spectrum $G_\delta(f)$ of the sampled signal $g(n/f_s)$ is as shown in Figure 3b.

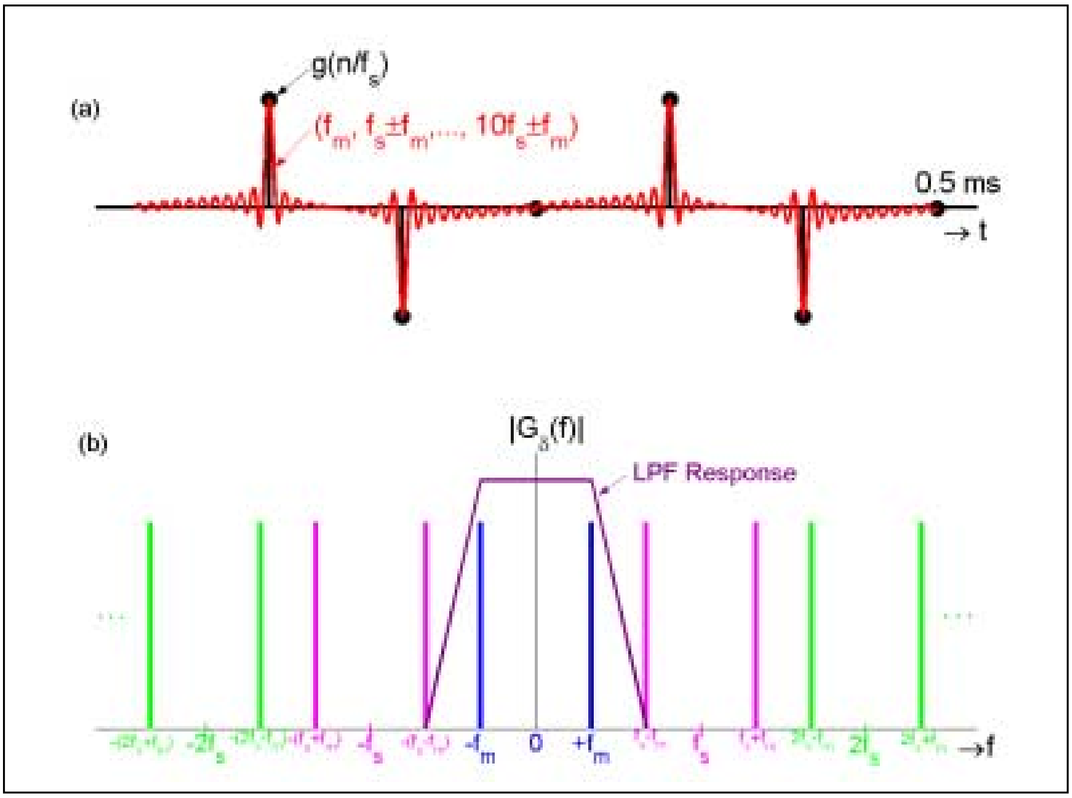


**Figure 3: (a) Sampled signal $g(n/fs)$ and its synthesis as a sum of sinusoids $jf_s \pm fm$, $j$ = 0, 1, 2, ..., 10. (b) Spectrum of sampled signal with $fs = 3f_m$.**

We see therefore that sampling an analogue signal of frequency $f_m$ has the effect of replicating (without any distortion) the baseband frequency $f_m$ at intervals of $f_s$. As illustrated in Figure 3b, the frequency $f_m$ and hence the original signal $g(t)$ can be recovered from $g(n/f_s)$ by passing the samples through a low pass filter (LPF)— known as a *reconstruction filter*, which passes only $f_m$ and blocks all the image frequencies. Since the lowest image frequency is $f_s – f_m$, this clearly requires that $f_s - f_m \geq f_m$, or

$$f_s \quad \geq \quad 2f_m \qquad (1)$$

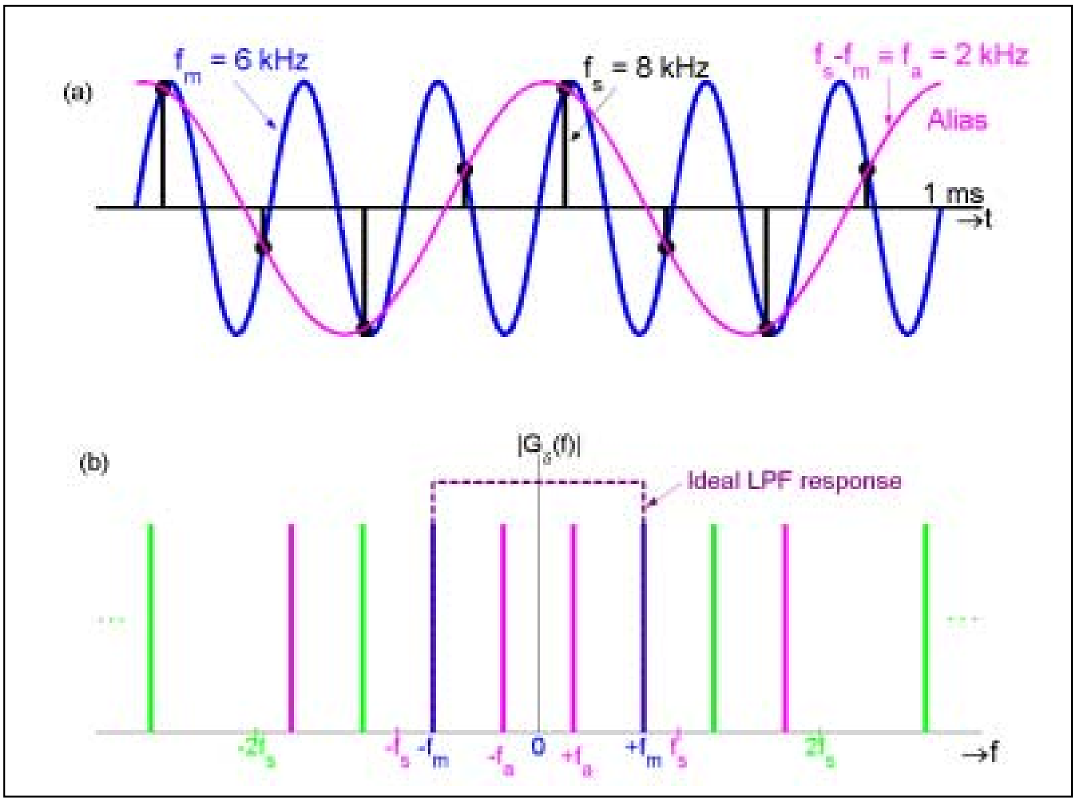


**Figure 4: (a) Sinusoid $g(t)$ of frequency $f_m$; under-sampled signal $g(n/f_s)$; and the resulting alias of frequency $f_a$. (b) Spectrum of $g(n/f_s)$.**

Figure 4 illustrates the effect of choosing a sampling rate $f_s$ less than $2f_m$, in direct violation of Eqn (1). In this example, $f_m$ = 6kHz and $f_s$ = 8kHz. The lowest image frequency $|f_s – f_m|$ is smaller than $f_m$ and is known as an *alias frequency* $f_a$ since the LPF will recover this frequency in place of (or, depending on the LPF bandwidth, in addition to) $f_m$. Thus, the reconstructed signal will contain a frequency component $f_a$ not present in the original signal, and is therefore distorted. Note that this distortion, known as *alias distortion*, is the result of *under-sampling*. Sampling at a sufficient rate as stipulated by Eqn (1) eliminates this problem.

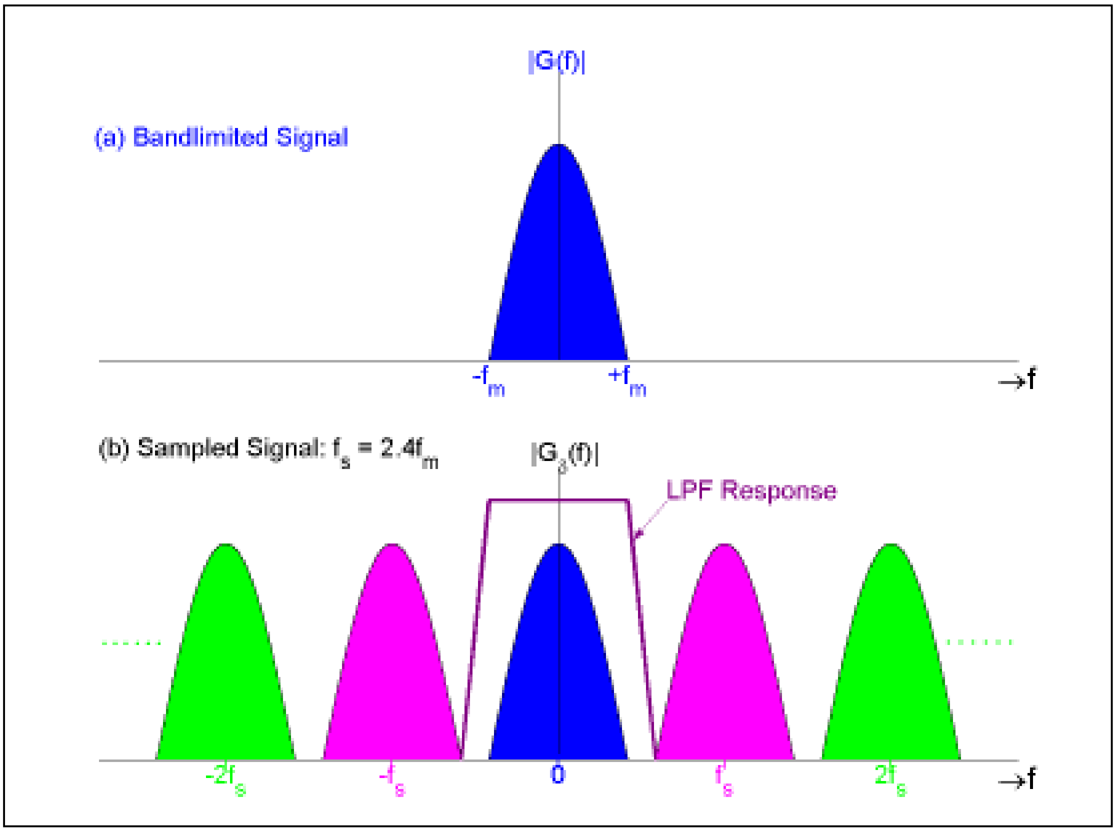


**Figure 5: (a) Band-limited signal; (b) Spectrum of $g(n/fs)$ for $fs > 2f_m$**

The discussion so far has focused on a sinusoidal signal. However, an arbitrary information signal $g(t)$ is realisable as a (discrete or continuous) sum of sinusoids, leading to a band of frequencies or spectrum $G(f)$. When $g(t)$ is sampled, then each frequency component of $G(f)$ is replicated as discussed above at intervals of $f_s$. The result is that the entire baseband $G(f)$ is replicated at intervals of $f_s$ and image bands are formed at $jf_s$, $j$ = …,–3, –2, –1, 0, 1, 2, 3, … If $g(t)$ is band-limited with bandwidth $f_m$ as shown in Figure 5a, then the replicated bands do not overlap provided $f_s \geq 2f_m$. Under this condition, $G(f)$ and hence $g(t)$ can be recovered from $G_\delta(f)$ (or equivalently $g(nT_s)$) using a LPF as illustrated in Fig 5b.

Sampling at a rate $f_s = 2f_m$, called the *Nyquist rate*, requires an ideal reconstruction filter as shown in Figure 6a. A sampling rate $f_s < 2f_m$ (Figure 6b) causes alias distortion due to an overlap between the baseband and the lowest image band. In conclusion, we may state the sampling theorem as follows:

> *A band-limited low pass signal that has no frequency components above fm (Hz) may be perfectly reconstructed, using a low-pass filter, from its samples taken at regular intervals at the rate* $fs \geq 2f_m$ *(samples per second, or Hz).*

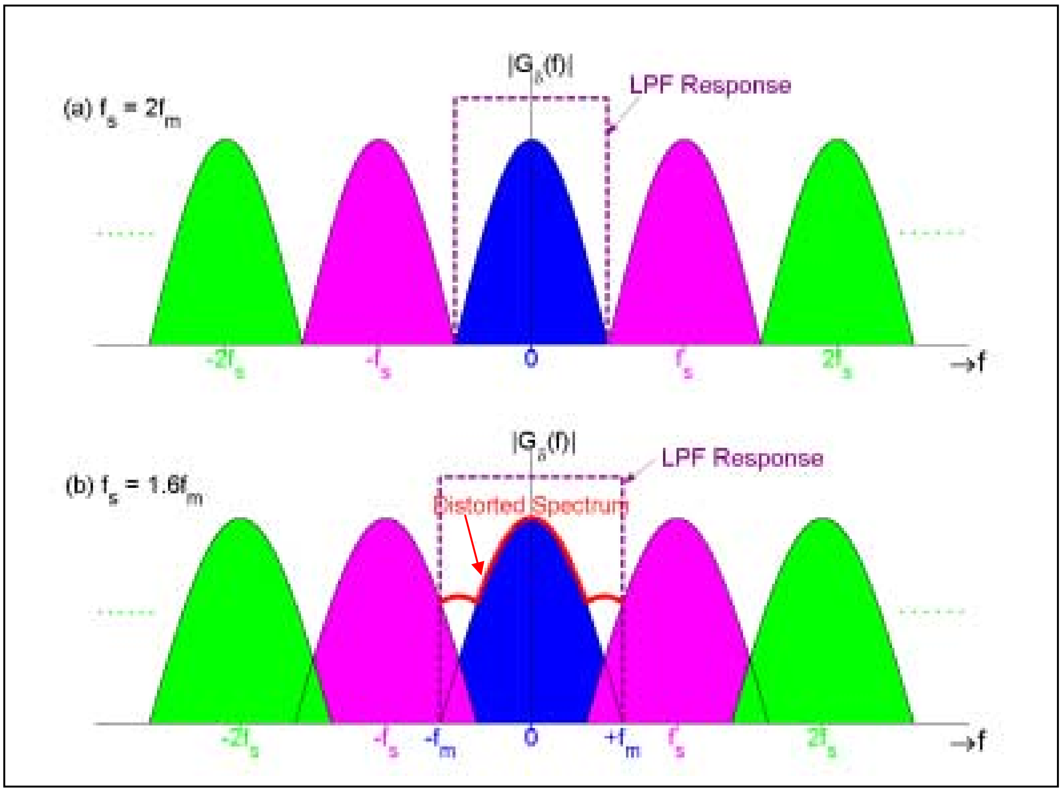


**Figure 6: Sampling at (a) Nyquist rate; and (b) below Nyquist rate**

The above discussion covered only instantaneous sampling, but can be extended [7] with minimal mathematics to natural and flat-top sampling, aperture effect, anti-alias filter design, etc. Now consider an alternative maths-first approach.

# Maths-First Introduction To Sampling

A set of functions $\{\phi_n(t)\}$, where $n$ is an integer, is said to be orthogonal with respect to each other in the interval $a < t < b$ if

$$\int_a^b \phi_n(t)\phi_m^*(t)\,dt = \begin{cases} 0, & n \neq m \\ E_n, & n = m \end{cases} \tag{2}$$

where $E_n$ is a constant larger than zero, and the asterisk denotes complex conjugation. Given a physically realisable signal $g(t)$ defined over the interval $(a, b)$ and a complete orthogonal set $\{\phi_n(t)\}$, then we may form the series

$$g(t) = \sum_n c_n \phi_n(t) \tag{3}$$

where the summation covers all the functions in the orthogonal set. Multiplying both sides of Eqn (3) by $\phi_m^*(t)$ and integrating over the interval $(a, b)$:

$$\int_a^b g(t)\phi_m^*(t)dt = \int_a^b \left[\sum_n c_n\phi_n(t)\right]\phi_m^*(t)\,dt$$
$$= \sum_n c_n \int_a^b \phi_n(t)\phi_m^*(t)\,dt \quad (4)$$
$$= c_m E_m$$

In the above, we interchanged the order of integration and summation (line 2) before employing Eqn (2) to obtain the last line. We see therefore that the signal $g(t)$ can be represented by the orthogonal series of Eqn (3) with the coefficients given by

$$c_n = \frac{1}{E_n}\int_a^b g(t)\phi_n^*(t)\,dt \quad (5)$$

Examples of a complete orthogonal set include harmonic sinusoids (leading to the Fourier series), Legendre polynomials, Bessel functions and sinc functions. We will consider the sinc function set and its application in more depth. The sinc function is defined as follows:

$$\text{sinc}(x) = \frac{\sin(\pi x)}{\pi x} \quad (6)$$

Consider the set of functions defined by

$$\phi_n(t) = \text{sinc}(t/T_s - n) \quad (7)$$

where $n$ is an integer and $T_s$ is a time parameter. To show that $\phi_n(t)$ form an orthogonal set in the interval $(-\infty, \infty)$ we apply the well known Parseval's theorem, which states that

$$\int_{-\infty}^{\infty} \phi_n(t)\phi_m^*(t)\,dt \quad = \quad \int_{-\infty}^{\infty} \Phi_n(f)\Phi_m^*(f)\,df \tag{8}$$

Here $\Phi_n(f)$ is the Fourier transform of $\phi_n(t)$ and is given by

$$\Phi_n(f) = T_s\,\mathrm{rect}(fT_s)e^{-j2\pi fnT_s} \tag{9}$$

where $\mathrm{rect}(fT_s)$ is a unit rectangular function defined by

$$\mathrm{rect}(fT_s) \quad = \quad \begin{cases} 1, & -\dfrac{1}{2T_s} \le f \le \dfrac{1}{2T_s} \\ 0, & |f| > \dfrac{1}{2T_s} \end{cases} \tag{10}$$

Substituting Eqn (9) in the RHS of Eqn (8) leads to

$$\begin{aligned} \int_{-\infty}^{\infty} \phi_n(t)\phi_m^*(t)\,dt \quad &= \quad \int_{-\infty}^{\infty} \left[T_s\,\mathrm{rect}(fT_s)e^{-j2\pi fnT_s}\right]\left[T_s\,\mathrm{rect}(fT_s)e^{j2\pi fmT_s}\right]df \\ &= T_s^2\int_{-1/2T_s}^{1/2T_s} e^{-j2\pi fT_s(n-m)}\,df \\ &= \begin{cases} T_s, & n = m \\ 0, & n \ne m \end{cases} \end{aligned} \tag{11}$$

Thus the sinc functions in Eqn (7) form an orthogonal set and, following Eqn (3) and (5) with $E_n = T_s$, we may represent any physically realisable signal $g(t)$ having a Fourier transform $G(f)$ as follows:

$$\begin{aligned} g(t) \quad &= \quad \sum_{n=-\infty}^{\infty} c_n\,\mathrm{sinc}(t/T_s - n) \\ c_n \quad &= \quad \frac{1}{T_s}\int_{-\infty}^{\infty} g(t)\,\mathrm{sinc}(t/T_s - n)\,dt \end{aligned} \tag{12}$$

Applying Parseval's theorem — Eqn (8), and noting that the Fourier transform of sinc($t/T_s - n$) is given in Eqn (9), the coefficient $c_n$ may be expressed as follows

$$\begin{aligned} c_n &= \frac{1}{T_s}\int_{-\infty}^{\infty} G(f)\left[T_s \operatorname{rect}(fT_s)e^{j2\pi f(nT_s)}\right]df \\ &= \int_{-1/2T_s}^{1/2T_s} G(f)e^{j2\pi f(nT_s)}df \end{aligned} \tag{13}$$

Now if the signal $g(t)$ is band-limited such that its spectrum

$$G(f) = 0 \text{ for } |f| \geq \frac{1}{2T_s}$$

$$\text{In other words, signal bandwidth } f_m \leq \frac{1}{2T_s} = \frac{f_s}{2} \tag{14}$$

then we may extend the limits of integration in the last line of Eqn (13) to ±∞ with no effect on the result of the integral. Thus,

$$\begin{aligned} c_n &= \int_{-\infty}^{\infty} G(f)e^{j2\pi f(nT_s)}df \\ &= g(nT_s) \end{aligned} \tag{15}$$

The last line follows by definition of the Fourier transform. Substituting for $c_n$ in Eqn (12) yields the following important result:

$$g(t) = \sum_{n=-\infty}^{\infty} g(nT_s)\operatorname{sinc}(t/T_s - n) \tag{16}$$

Eqn (16) states that we can reconstruct the original signal $g(t)$ from its samples $g(nT_s)$ taken at a regular *sampling interval* $T_s$, which corresponds to a *sampling frequency* $f_s = 1/T_s$. Bear in mind that Eqn (14) is a necessary condition for Eqn (16) to hold. Taking these two equations together, we can state the *sampling theorem* as follows:

> *A realisable band-limited signal that has no frequency components above $f_m$ is completely described by, and may be perfectly reconstructed from, its samples taken at regular intervals at the rate $f_s \geq 2f_m$. The lowest sampling rate $f_s = 2f_m$ is called the Nyquist rate.*

The reconstruction is achieved as follows using an *interpolation function* sinc($t/T_s$). The $n^{th}$ sample $g(nT_s)$ is multiplied by the interpolation function sinc($t/T_s$) delayed by $nT_s$. All the waveforms obtained in this manner for $-\infty < n < +\infty$ are summed to give the original signal $g(t)$ for $-\infty < t < +\infty$. To reconstruct $g(t)$ within a finite interval requires the inclusion of not only the interpolating functions with peaks falling within the interval, but also those functions on either side of the segment having significant tails within the segment. Figure 7 is an illustration of the reconstruction of a 0.5ms segment of a sinusoid of frequency 4 kHz from its samples taken at a sampling rate $f_s$ = 12 kHz. Note the accuracy of the reconstruction and the inclusion of significant tails of sinc functions whose peaks lie outside the segment on either side.

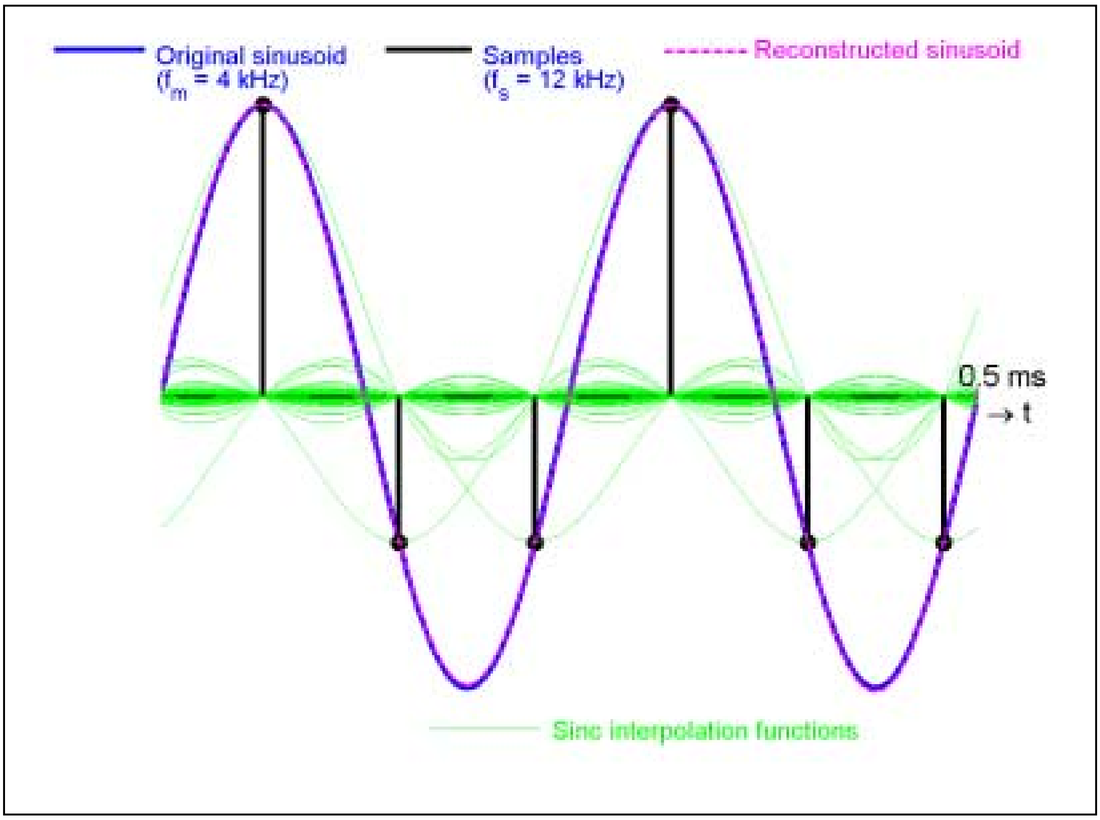


**Figure 7: Reconstruction of a sinusoid from its samples**

Figure 8 shows the application of Eqn (16) to the case of a band-limited signal of bandwidth 5kHz sampled at 12 kHz. The reconstruction is again accurate. Figure 9 illustrates the consequence of under-sampling, i.e. choosing $f_s < 2f_m$ in violation of the sampling theorem; in this case a 4kHz sinusoid is sampled at 6kHz. We see that the reconstructed signal is different from the original. The recovered signal is referred to as an *alias* and has a frequency $f_a = |f_s - f_m| = 2$kHz. This misconstruction due to under-sampling gives rise to *aliasing distortion*.

A little thought shows that the reconstruction process generates an output sequence of sinc pulses at a regular interval $T_s$, each pulse weighted by $g(nT_s)$. Since an ideal LPF — with a rectangular-shaped frequency response — has a sinc-pulse-shaped impulse response, it is clear that this output is that of an ideal LPF with input $g(nT_s)\delta(t-nT_s)$ for $-\infty < n < +\infty$, where $\delta(t)$ is the Dirac delta function. In other words, the reconstruction is accomplished by passing the sequence of samples $g(nT_s)$ through an ideal low pass filter.

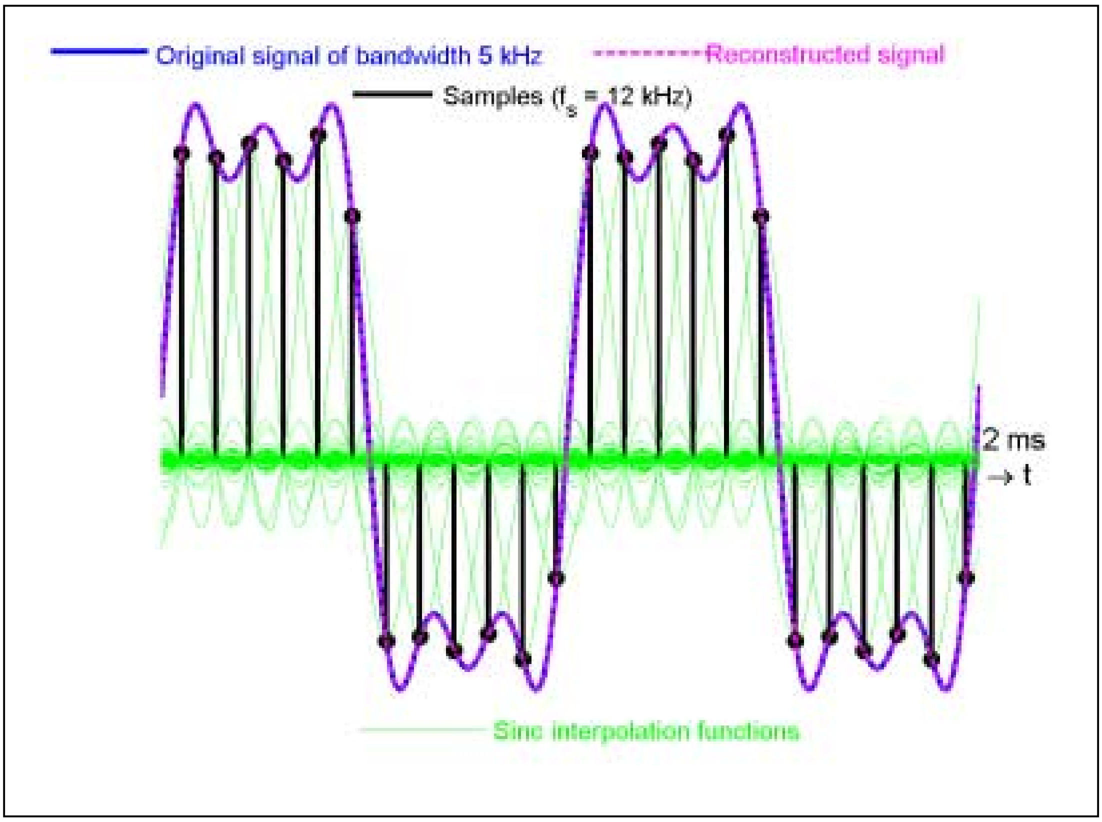


**Figure 8: Reconstruction of a band-limited signal**

To further clarify the sampling and reconstruction process, note that the signal $g_\delta(t)$ obtained through ideal (or instantaneous) sampling of the signal $g(t)$ can be expressed as the product of $g(t)$ and a switching impulse train of period $T_s$:

$$g_\delta(t) = g(t) \times \delta_{T_s}(t) = \sum_{n=-\infty}^{\infty} g(nT_s)\delta(t - nT_s) \qquad (17)$$

where we have made use of the sifting property of the impulse function, which states that

$$g(t)\delta(t-t_o) = g(t_o)\delta(t-t_o) \tag{18}$$

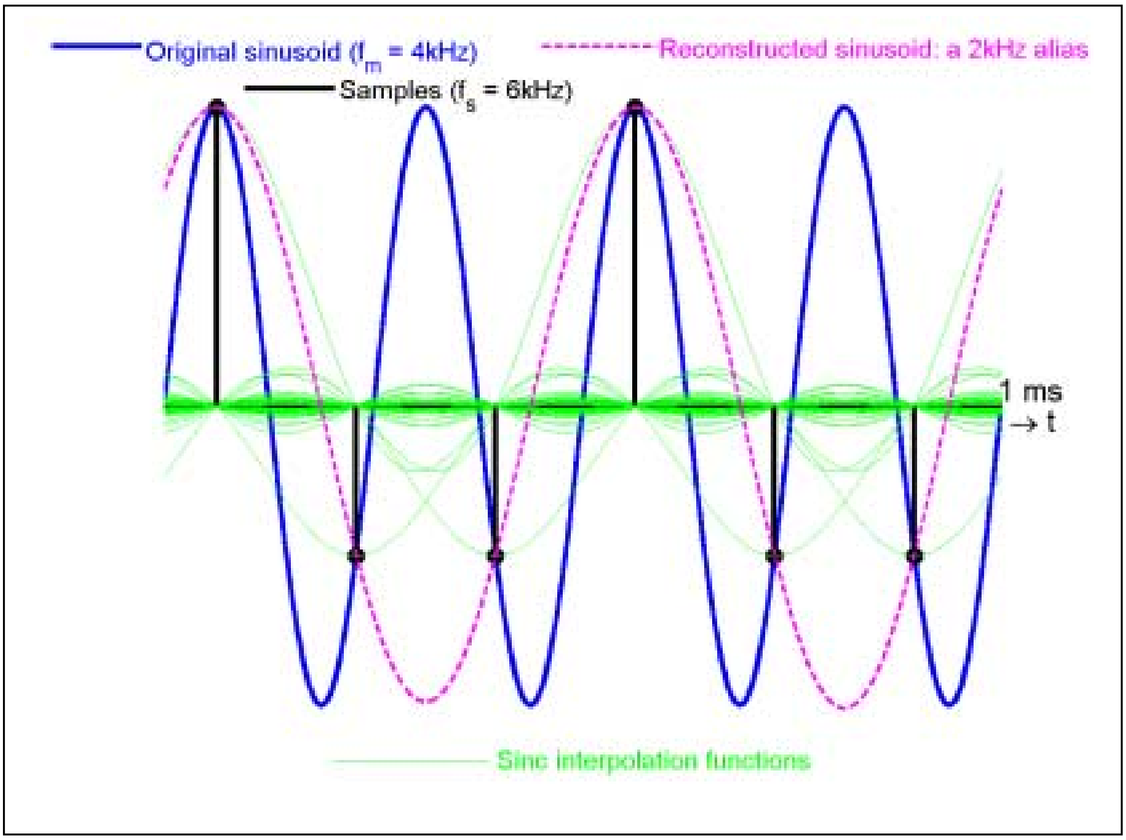


**Figure 9: Effect of under-sampling**

Returning to Eqn (17) and noting that multiplication in the time domain transforms into convolution $(\star)$ in the frequency domain, we obtain the Fourier transform of the sampled signal as

$$\begin{aligned} G_\delta(f) &= G(f) \star f_s \sum_{n=-\infty}^{\infty} \delta(f - nf_s) \\ &= f_s \sum_{n=-\infty}^{\infty} G(f - nf_s) \\ &= f_s G(f) + f_s \sum_{\substack{n=-\infty \\ n \neq 0}}^{\infty} G(f - nf_s) \end{aligned} \tag{19}$$

where, in the second line, we made use of the fact that convolution of a function with an impulse merely shifts the function to the location of the impulse. Eqn (19) shows that the sampled signal has a spectrum that consists of the original signal spectrum (with a scaling factor) plus replications at intervals of $f_s$. The original spectrum and hence signal $g(t)$ can be reconstructed or extracted by passing the sampled signal — hence $G_\delta(f)$ — through a LPF, provided there is no overlap between replicated spectra. An overlap is avoided if the sampling frequency $f_s \geq 2f_m$, where $f_m$ is the signal bandwidth. Choosing $f_s > 2f_m$ permits the use of a realisable LPF with a transition band, rather than an ideal LPF, which is required if $f_s = 2f_m$.

# Conclusion

The two approaches yield the same results: that (instantaneous) sampling is a distortion-free process provided the sampling rate ($f_s$) is at least double the signal bandwidth ($f_m$); and that the device that reconstructs the original (low pass) signal from the sequence of sample values is a low pass filter (LPF). An unrealisable ideal brickwall LPF is required to avoid distortion if $f_s = 2f_m$, while a choice of $f_s > 2f_m$ allows a realisable filter design. However, aliasing distortion is unavoidable if $f_s < 2f_m$.

Taken together the two approaches give a more complete and highly satisfying understanding of the topic. The second approach is elegant and rigorous, and exhibits the beauty of mathematics and its enduring application to real-world engineering. This approach starts with maths and eventually ends with an engineering application, after several lines of exciting (?) mathematical discourse. If the majority of students were both familiar and comfortable with the range of mathematical concepts invoked (integration, Fourier transform, Parseval's theorem, impulse function and its characteristics, etc.), then this approach would be excellent. However, given the maths problem highlighted earlier in this report, a lecturer who follows this approach in a first-year class would most likely seem like a brilliant mathematician lost in their[1] own bliss and out of touch with the real world of their befuddled class. They[2] would risk inflicting a high attrition rate on their engineering department. Many of the students would be only marginally more enlightened than if the sampling theorem were simply quoted without proof. In fact some could even be worse off due to discouragement and self-doubt.

The beauty of the first approach is that it emphasises engineering considerations throughout and presents an intuitively satisfying and insightful discussion of the topic. This approach espouses the beauty of engineering, and sets mathematics in its rightful place as a tool that can be used and discarded as necessary for the benefit of engineering. Contrast this with the second approach, which extols the beauty of mathematics, and introduces engineering as an application of the great

---

[1] His or her

[2] He or she

subject. One approach should come naturally to a mathematician teaching engineering and the other to an engineering academic. Regrettably, this is not always the case. Engineering students are predominantly being served a main meal of maths with some engineering for dessert. Sadly, a significant number of these students suffer from a condition of prolonged *mathophobia*, and therefore will not sign up at all or will initiate an emergency exit soon after joining the party.

There seems to be a mistaken notion that adapting our teaching approach to the ability and preference of the majority of our student intake would be tantamount to a lowering of academic standards. This widely held apprehension stems from the belief that the alternative to a maths-first approach is one that arms students with magic formulas, which they can apply superficially to solve standard engineering problems. However, I have tried to show in this report that there is another way, which can be applied with a high academic standard to any engineering topic, especially those traditionally wrapped in maths. The paucity of good engineering textbooks based on an engineering-first approach is currently a handicap, but if your subject area is communication systems then you may find reference [7] useful.

# Acknowledgment

I am grateful to LTSN Engineering for the funding that allowed me time to prepare this report.

# References

1. Engineering Council (UK), "Measuring the mathematics problem", *Engineering Council Report*, London, 2000

2. Otung I. E., "Reassessing the mathematics content of engineering education", *Engineering Science and Education Journal*, Vol 10, No 4., August 2001, pp. 130-138

3. Mustoe L., "Crisis in A level mathematics", *MSOR Connections*, Vol 2, No 1., February 2002, pp. 14

4. Wolf A. and Tikley C., The Maths We Need Now, *Institute of Education London*, 2000

5. Otung I. E., "Maths for engineering students", *Engineering Science and Education Journal*, Vol 10, No 5., October 2001, pp. 207

6. Kent P., "Mathematical components of engineering expertise", *MSOR Connections*, Vol 2, No 2., May 2002, pp. 26-27

7. Otung I. E., Communication Engineering Principles, ISBN 0 333 77522 8, *Palgrave Basingstoke*, 2001