

# EPOS 2006

## Epistemological Perspectives on Simulation

II Edition

University of Brescia, Italy

October 5-6, 2006



### The Nature of Noise

Bruce Edmonds\*

#### 1. Introduction

The idea of noise plays a prominent (if subsidiary) part in many fields of study; it is casually mentioned in numerous papers as if its nature was well established. However to a large extent the term is not examined, but simply used. In other words, it has become part of the *practice* of science without entering to a significant<sup>1</sup> extent as part of its explicit *theory*<sup>2</sup>.

The Oxford English Dictionary presents the following account (after a list of descriptions of more mundane uses referring to the older, non-technical uses of the word noise):

\* Centre for Policy Modelling, Manchester Metropolitan University, UK: <http://bruce.edmonds.name>.

<sup>1</sup> The exception being in Electrical Engineering where some attention has been paid to this area, however this is specific to where it is possible to include some properties of the noise within an explicit (statistical) model. For more on this see the second section.

<sup>2</sup> (Habermans 1963), this relates closely to the distinction in (Cartwright 1983) on bridging rules and theory.

*“11. a. In scientific and technical use: random or irregular fluctuations or disturbances which are not part of a signal (whether the result is audible or not), or which interfere with or obscure a signal; oscillations with a randomly fluctuating amplitude over a usually continuous range of frequencies. Also in extended use: distortions or additions which interfere with the transfer of information....*

*b. In non-technical contexts: irrelevant or superfluous information or activity, esp. that which distracts from what is important.*

Thus we have a veritable “hairball” of related ideas, including: randomness; irregularity; disturbance; interference; obscuration; non part of a signal; distortion; addition; irrelevance; superfluity; and distraction applying to either a signal or to “what is important”. I think this accurately represents the term as it is used in technical papers (both in terms of content and in its vagueness). In this paper I try to produce a clearer and more coherent account of the term – an account that moves towards a more general theory of noise.

I start with a picture of noise from electrical engineering, since this seems to be where the concept arose first in academic papers<sup>3</sup> and so frames much of the scientific thinking on the subject. I then generalise this picture to the widest conception: that of noise as what is unwanted, which relates to our aural experience. A closely related conception that has developed in the scientific literature is noise as what is unexplained – the residual after what can be explained (or modelled) is factored out. A particular case of this later usage is where a source of randomness can be used to stand-in for this residual. This strategy has led some to almost identify noise and randomness. However I argue that noise and randomness are *not* the same and thoughtlessly conflating them can result in misleading assumptions. I explore the possible relation between noise and context, and propose a new conception of noise, namely that noise is what can result from an extra-contextual signal. I claim that this is not only a psychologically plausible account of its origin (and hence relates well to common usage) but is also a useful way of conceptualising it. I finish with an application of the analysis of noise to the relation of determinism and randomness.

## **2. A picture of noise from electrical engineering**

The close correspondence between electrical and acoustic phenomena allows the transfer of the term “noise” from an audible description to that which describes elements in the electrical phenomena that generates the sounds via a loud speaker. When you hear reproduced sound that is generated by electrical apparatus and compare it to the original sound, it has changed: a “hiss” has been added that sounds like (and acts like) noise. Thus noise becomes a technical term by analogy, however

<sup>3</sup> The Oxford English Dictionary’s first quote from the academic literature is from the *Telegraph and Telephone Journal* in 1923 (vol. 9 pp. 119/2) “*The variations in noise were plotted, and their effect at times was to reduce the intelligibility to 20 or 30 per cent.*”. Obviously, the non-technical senses of the word are much older.

the way it was done is important and seems to have influenced the idea's subsequent development.

The focus of much work in electrical engineering is the manipulation of identifiable electrical *signals*. These signals are the patterns or values encoded by the properties of a real electric current or field. To be precise, the signals are the intended patterns or values that are represented in actual (i.e. implemented or observed) flows of electrons and the forces between electrons. This distinction between *electrical signal* and *electrical phenomena* is important because it marks the shift from a scientific point of view, where one is trying to discover the properties of the observed world, to an engineering perspective, where one is trying to manipulate parts of the world to obtain a desired effect. Of course, there is no well-defined boundaries between these two approaches, and in practice many who work with electrical phenomena will, at different times and for different purposes, swap between scientific and engineering viewpoints. It is noticeable that 'noise' enters the scientific literature only when we were able to control these effects sufficiently in order to be able to manipulate electrical phenomena in intended ways.

In electrical engineering you have a set of *inputs* and *outputs* that pass through a set of (usually well-defined) circuitry. The aim is to effect an intended transformation upon the inputs, which become the outputs. The transformations are implemented by (on-the-whole carefully manufactured) components such as transistors, diodes etc. The heat and nature of these devices means that the intended transformation is imperfect. For example an amplifier may be supposed to evenly increase the amplitude of a signal but otherwise leave it unchanged, but in reality will also distort it, add 'hiss' that is audible when broadcast etc. This situation is illustrated below in

Figure 1.

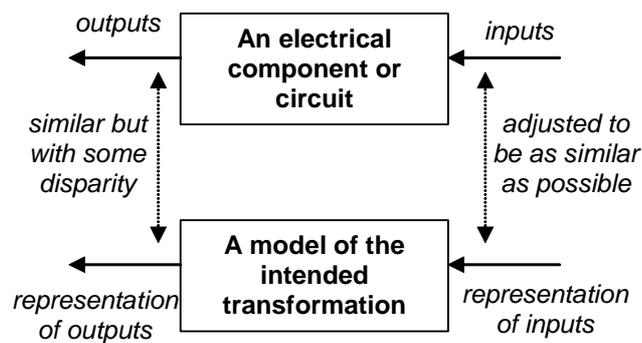


Figure 1. The disparity between the actual and ideal outputs of a circuit

In electrical engineering there are relatively good models for the action of such components (or conversely, we have learnt to manufacture components so that they are well represented by our models). Often these models not only specify the principal transformation effected by a component but also the give some information about the nature and extent of the imperfections, particularly the result of heat (and

other entropy producing processes). This kind of understanding goes back to (Einstein 1905) and seems to pre-date the technical use of the word “noise”. Although the detail of this noise is unpredictable, it is particularly well characterised in terms of its general properties and is closely mimicked by a random statistical process – we call this ‘white’ noise. Thus many models of electrical components *reify* this as a distinct ‘noise term’, which may be otherwise undefined, or may with a defined probability distribution and related its magnitude to conditions such as temperature. The source of this particular kind of imperfection is relatively well understood, predictable and perceptible – it thus is natural to conceptually separate it out and label it as ‘noise’. Thus the notions of the intended signal and the actual phenomena diverge. I illustrate the result of this process of abstraction in

Figure 2.

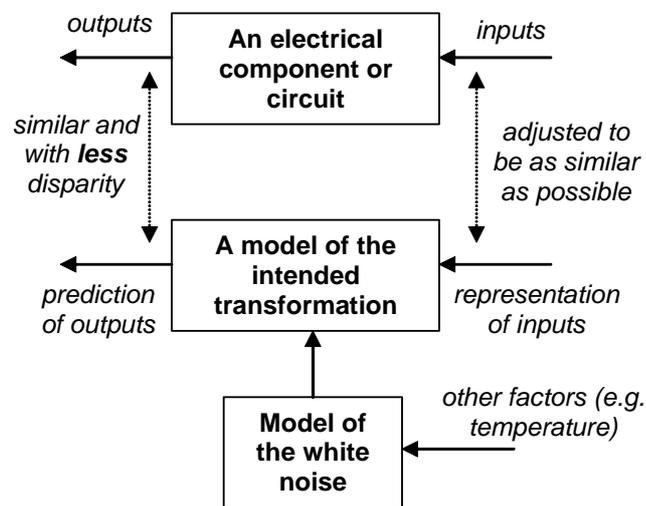


Figure 2. The smaller disparity when noise is reified and explicitly represented

This shows that it can be undoubtedly useful to think of noise as a separate and identifiable extraneous factor that is ‘added’ to the signal to obtain a more realistic prediction of the results. The combined model is composed of two submodels: the original and the model of the residual<sup>4</sup>. This coincides with the ‘shift’ from a *scientific* viewpoint of such circuits to an *engineering* viewpoint. As Wong (2003) puts it:

<sup>4</sup> Alternately one can consider the conceptual and phenomenal models as separate (Hughes 1997).

*“Particularly, to the physicist the noise in an electronic system represents a practical manifesting of the phenomena described by statistical mechanics, and an understanding of its practical consequences helps to illuminate and clarify some concepts of the physical theory; to the electronics engineer, noise is a constraint of the real systems, but a better understanding of its physical origins helps the engineers to minimize its effects by informed and careful design.”*

Within electrical engineering there is a continuing awareness that the randomness is just a model for the noise and that this model has its limitations. Pierce makes it clear that the noise is the primary descriptor and randomness part of the model when he says (1956):

*“Many sorts of electrical signals are called noise ... many engineers have come to regard any interfering signal of a more or less unpredictable nature as noise. ... The theory of noise presented here is not valid for all signals or phenomena which the engineer may identify as noise.”*

This practice is now quite common in many fields, often indicated by the appearance of a ‘noise’ term<sup>5</sup> in equations. However it should be remembered that this case is quite a special one. This particular kind of distortion particularly well-understood, predictable and separable. It is also only one particular kind of distortion that can occur, albeit often a dominant one – other kinds such as resonance, interference, distortion etc. also occur and are more difficult to predict/model partly because they are less separable from an intended (or significant<sup>6</sup>) *pattern*. Mimicking this step of using a single reified source called noise to stand for a general disparity between explained and actual outcomes is likely to be much less useful in many other domains.

Some of what makes this a special case (i.e. justifies the attribution of ‘noise’ to error) is summarised as follows:

- The input signal and the intended results are known;
- There are good predictive model of the intended transformations involved;
- The whole system is engineered in a controlled way – the composition of the parts is explicitly known;
  - The principal disparity between ideal and actual is well-understood;
  - Many of the disparity’s characteristics are predicatively modelled as a separate part of the model;

<sup>5</sup> Although frequently this has no predictive function but is merely an apology for the disparity between the prediction and what is observed, i.e. it does not predict the extent or nature of the disparity (as is frequently the case in electrical engineering) but is there as an admission of incompleteness. In these cases it is more correct to call this an ‘error term’.

<sup>6</sup> Of course, what is considered significant is a movable feast – but this is the point: attributions of ‘noise’ are results of relevance decisions, even if these are implicit.

- This disparity can be characterised numerically so that the total disparity for a system can be estimated mathematically;
- This disparity is easy to identify and even directly perceive.

These conditions have made the reification of noise as kinds of randomness a useful, if minor, field of study<sup>7</sup>. Analogous conditions are evidently not true for many other domains of study, and yet this idea of a separable source of noise being mixed in with a significant signal has become a common one. In the next section I consider a generalisation of the concept of noise to include the wider cases.

### 3. Noise as unwanted interference

Noise can be seen as a largely a negative idea – as humans we are often interested in specific sound *signals* in terms of communication, music etc. and other sounds may make the task of identifying these signals more difficult. The difference between a set of measurements and an ideal is often attributed to ‘noise’ – in this case it is precisely what is *not* the ideal. This is the older use of the term, that precedes its entrance into the academic literature. If you are trying to listen to the radio and there are busses travelling outside or even people talking you may lump these together as 'noise', since they are extraneous to what you were concentrating upon. One pair of people talking may be noise from the point of view of another pair of people talking and *vice versa*.

Noise here actually or potentially gets in the way of a perception or observation. A signal that has no chance at all of interfering with another is simply an irrelevant signal. Even if my neighbour's car generates a lot of sound inside its engine as a side effect of its operation, it is not noise if its silencer is such that this never escapes so as to disturb me. Thus a silencer on a car *eliminates* noise, even if the sound levels *inside* that engine remain the same. It is critical that if one counterfactually *imagines* the sound as escaping then it is natural to think of this as potential noise.

This conception of noise has, by analogy, now extended beyond aural noise – it is now commonly used as a generalisation of this idea. Thus an electric drill might be said to generate electrical ‘noise’ which might interfere with the reception of my TV. The essential aspects of this generalised conception seem to be that:

- there is an identifiable source of the ‘noise’
- that interferes with the reception of a target signal
- such that the noise is not intrinsic (or essential) to the signal and its transmission.

A non-electrical example of this kind of noise is interferences in gene expression (Blake et al. 2003).

<sup>7</sup> Useful collections of sources about electrical noise are: (Gupta 1977, Ritter 2003).

#### 4. Noise as un-modelled residual

To a modeller, noise is that which prevents one from modelling a process with complete accuracy. In a way the noise is something that is interfering with the modelling results, and so can be seen as analogous to the characterisation of noise in the previous section. Thus an econometric model may be composed of an identified trend plus a noise term to 'account' for the deviations from this trend.

This is a presumptuous use of the term – it implies that the 'noise' is something which may mask the hypothesised trend but is judged to be ultimately irrelevant to it. It thus suggests that the disparity is not simply due to modelling error, i.e. that there is not an accessible better model that would do better.

Nonetheless attributing modelling error to noise is sometimes appropriate – if you count the number of children at a children's party where children are not allowed to enter or leave and you get a different count each time then one can safely attribute the error to measurement “noise” (expressed in the chaotic movement of the children) rather than fundamental model error (the model being that there is a fixed integral number,  $n$ , of children in the room). You can sensibly model the sequence of counts as a fixed constant plus a noise term (which might usefully be given a random nature).

Whatever the purpose of the modelling, a discrepancy between the model outputs and target data gained from measurement of the modelling target is an indication that there is something in the target + measurement processes that is not captured by the model. In other words, the data itself is another model, a “data model” (Suppes 1962). If one has some good reasons to attribute this discrepancy to some factors that are not relevant to (in the sense of “arbitrary with respect to”) the model and its purpose, then it can be properly called noise.

When modelling complex phenomena (e.g. social phenomena) it is inevitable that one is not going to be able to capture all aspects of ones target in any single model and hence one would expect that there will be a disparity between a model's outputs and the corresponding data obtained from the target. The key question is whether this discrepancy is due factors that are relevant to the modelling task or originate from a process that is independent and irrelevant.

Conflating noise and fundamental model error can be very unhelpful. I will illustrate this with an example from the insurance industry.

**Example 1:            *The estimation of insurance claims***

This case concerns the estimation of the frequency of events in the insurance industry. Before 1990, the distribution of insurance claims was thought to be roughly normal, that is when one plotted the frequencies of periods with different levels of claims the result fitted a normal curve well except for a few periods with a very high level of claims. However these few cases were discounted as due to particular circumstances and hence unmodellable. This model of a normal distribution plus some arbitrary events was used to set premiums. However more recently a series of models which explicitly includes and predicts such “extreme” events have been re-discovered and applied (Black 1986, Andersen and Sornette 2001).

**Example 2:            *The ‘noise traders’***

There is a model of stock markets which has two types of trader (DeLong et al 1990): those that invest according to the ‘fundamentals’ of stocks and ‘noise’ traders who speculate randomly. Their combined actions serve as a candidate explanation for the sort of movements observed in stock market indices. The individuals in the model that stand for these traders can swap between these two types, so a trader that was formerly a fundamental trader may become a noise trader and *vice versa*. The noise traders essentially act randomly, but the swapping between the behavioural types is as a result of the prevailing stock market conditions and the thresholds of that particular trader.

Many social models attempt to use statistical models to separate out social trends from the ‘noise’, under the assumption that human actions can be represented *en masse* as trends plus arbitrary actions that tend to cancel each other out (in large samples). If that ‘noise’ is supposed to be effectively random, then this is a hypothesis that can be tested, since in increasingly large samples the noise will not grow as fast as the signal and will thus fall as a proportion of the population size (something that is not obviously true of stock markets). This is called the “law of large numbers”. This may be justified as in (Dichev 2001) but in other cases it is not, as demonstrated by the models of (Kaneko 1994, Edmonds 1999a).

Indeed we are so used to the idea of separating out a signal from added random noise that we forget what a special case this is, as (Van Kempen 2001) put it:

*The amazing thing therefore is not that they [fluctuations] give rise to irregular phenomena. The amazing thing is that a collective behavior emerges, which is regular and can be described by general law...*

**5. Noise and randomness**

In the special case where we are trying to model a particular data-generating process, we may well get to the stage where we have included in the model any systematic pattern we can detect in the data. In such a case what is left is precisely what we can not systematically model, namely a residue that is effectively

unpredictable<sup>8</sup>. This residue is, by construction, not modelled. However it might be possible to adjust the model so that the secondary characteristics of this residue are modellable. For example, although each point is unpredictable, the statistical moments of an increasingly large sample of this data may converge to particular values. These values can be used to construct a sort of model of these residuals – a statistical model. Such a statistical model is composed of a particular probability distribution, from which values can be randomly (or pseudo-randomly) generated. This random series of values is not the same as the unmodelled residual but 'looks' the same to us as modellers – each has the same known distribution and the same unpredictable content within this. If we deem that the unpredictable residue is not relevant then we can say that in all relevant aspects the random series and the residue are the same. Thus it is that we often think of this unmodelable residue as random – they *look* the same to us and (by construction) from the point of view of the model their detail is equally irrelevant<sup>9</sup>.

Such a perspective might lead one to conflate such noise and randomness and identify noise *as* randomness. However, this is simply to confuse a model (randomness) with what is modelled (noise). That they are not necessarily the same as the following examples show.

***Example 3: The interspersed coded-messages***

Imagine two different messages (strings *a* and *b*) that are both encrypted (to strings *x* and *y*) by different people (*A* and *B* respectively) so that each appears to be a random sequence to anyone but the person who encoded it. Then the two sequences are interspersed to form a single sequence (*c*). To *A* the part of *c* that is *y* is just noise, there is nothing modellable about *y*, only *x* has meaning. To *B* the part of *c* that is *x* is the noise whilst the *y* part has meaning.

The part that is noise for one person is the signal for the other and *vice versa*. Thus either randomness is a relative concept or it is different from noise (which in this case is clearly relative).

One might think that such a type of sequence would not result from any natural process, but this is only an assumption. If it is possible to make an unguessable binary sequence, then it is possible to implement such a data-generating process as a program on a computer. Thus if we had such a computer attached to a Geiger counter and a small lump of radioactive material (to generate the random input), and we always plug more memory into it as required, we could produce such a sequence. Thus although highly contrived such an example is not beyond the bounds of possibility for a natural process.

<sup>8</sup> Or, to put it in a weaker form: effectively unexplainable.

<sup>9</sup> There are a few approaches that move towards *defining* randomness as the unmodellable residual, e.g. (Compagner 1991). It also turns out that patterns that are not compressible by a Turing Machine (Kolmogorov 1965) passes many of the traditional tests for randomness.

**Example 4:            *The sabotaged random number generator***

Imagine a company that sells good quality random sequences, that is sequences with well-defined long-term statistical properties but with no guessable patterns in the detail at all<sup>10</sup>. Say that they did produce sequences which passed all the requisite tests for randomness. Now say that an agent for a rival company interfered with the set-up by adding an extraneous signal to the process which caused the product to now fail some of the tougher tests for randomness.

That agent evidently introduced some noise into the system, but it was not purely random because it *decreased* the randomness of the result. Here randomness and noise are not the same but are opposed.

What is the case is that sometimes (as in the electrical engineering case above) it is useful to think of this unmodelled residual as arbitrary (particularly if one has good reason to believe that it is irrelevant to the modelling task in hand) and can be usefully represented by a random distribution. This is a natural thing to do since randomness is a positive way to think about noise which otherwise is a negative (what we don't want/understand/represent). In many modelling techniques (e.g. many simulations), it is useful to use a random source to 'stand-in' for parts of the model thought to introduce this arbitrariness. Then one can use techniques such as 'Monte Carlo Sampling' to try and separate out the effects of these parts from the tendencies exhibited by the rest of the model.

However arbitrariness and randomness are not the same as one can not guarantee that an arbitrary signal will not suddenly exhibit some pattern, which may turn out to be significant. This is shown clearly in the example of the 'Millennium Bridge' in London.

<sup>10</sup> There are such companies – I read of a Californian firm which claimed to use light detectors as a source of noise to provide the seeds for algorithms that produce 'high-quality' random numbers for sale (Peterson 1997).

### ***Example 5: The Millennium Bridge***

The Millennium Bridge is a beautifully elegant structure that spans the river Thames from the bank below St. Paul's to the Tate Modern gallery. This was carefully designed and the design was extensively simulated before being built. However, a few weeks after it was opened it had to be closed again for dampeners to be fitted, as it was prone to oscillations that were deemed a danger to the public. It seems that what happened is that in the simulations of the design the movements of people were assumed to be random, but with large numbers of people they reacted to small movements in the bridge so as to amplify the movement. The small oscillations had the effect of synchronising peoples' reactions and hence having a much greater effect. The result was that the unmodelled reactions of individuals and their coupling via small swayings of the bridge were far from random. Indeed, if they had not happened to cause this particular effect they could have safely regarded as arbitrary and hence modelled using a random 'stand-in', however that did not turn out to be the case (ARUP 2001, BBC News 2000).

## **6. Noise and context**

Let us look back at the picture of noise that we started with, that of electrical noise originating in electronic circuits. In one sense this is a very odd usage – noise here does not come from an arbitrary source but is part of the intrinsic nature of the electrical components. From a more objective point of view it is amazing that it is possible to construct ensembles of components that act so as to effect the desired transformations with such an astounding degree of accuracy. It would be less strange if such an ensemble only produced white noise whatever its input than it transforms the inputs to the desired outputs with such accuracy. It is only due to the huge scientific and engineering effort that has led to a situation where we can expect such perfection and hence reify any shortcomings as a separate entity called 'noise'.

Similar shifts occur in other situations; if one is trying to listen to person A talking then person B talking may be noise, and vice versa. What is noise depends on who one is trying to listen to.

A possible explanation for this is the context-dependency of modelling. Any model of observed phenomena has a set of conditions under which it is effectively applicable. Not all of these are explicitly included in models but rather the kind of context where a model is applicable is recognisable. The context ensures that, on the whole, these implicit conditions hold and that the model can be represented in a relatively simple and manageable form. The fuzziness of the context recognition allows the model content to be relatively well-defined and 'crisp'. This crispness allows us to reason about the content of such models. This necessary context-dependency in modelling is quite a separate matter from whether the model is generally applicable *in theory*. For example, the laws of Newtonian physics *presumably* hold to an astounding degree of accuracy (in circumstances where

relativistic and quantum effects are negligible), but may not be practically *applicable* in a situation where well-defined objects are difficult to identify.

The context-dependency of learning and application of knowledge and models makes these processes much more feasible. However, this 'trick' only works when the conditions under which a model is learnt are effectively recognisable, so that one knows when one can reliably apply a model. For more on the pragmatic roots of context see (Edmonds 1999b).

Error in a model's output's compared with observations could be due to several things: it could be due to sheer model error within the context; the context itself could have been wrongly identified; or the error could originate from without the assumed context. A coherent picture of noise comes about when the source originates from outside the assumed context – we do not want to reject the model (this still works at some level), and the assumed context seems to be the appropriate one (many other models associated with this context are working well) so the source of the error must lie elsewhere.

This picture of an extra-contextual cause of model error accounts for all the properties of noise we have identified above. In turn it accounts for:

- The arbitrariness of noise, since it comes from outside the context (since a modelling context is supposed to contain everything pertinent);
- The dependency of the identification of noise on context – thus in the “Two person's talking” example for each person the context focused on excluded the other talking;
- That the noise has to be able to interfere in the foreground model, since otherwise it has not entered the context as in the “Car Engine” example it depended on whether we imagined the sound escaping into our context (unless we imagined it doing so);
- That the shift from detecting the random fluctuations in the potential difference across a piece of conducting material at thermal equilibrium to the attempt to reduce interference with an audio signal in an amplifier corresponds to the reification of noise.

## **7. Noise and the “excluded middle” between randomness and determinism**

The thesis of determinism is widely held. To a thorough determinist any randomness is merely a result of incomplete modelling. In other words, *all* apparent randomness is *only* an unmodelled residue<sup>11</sup> – in principle it could all be modelled. Quantum mechanics forces many to accept that there is also unreducible randomness

<sup>11</sup> Indeed Compagner (1991) argues in the reverse direction – namely that randomness can be defined as what is uncorrelated.

in the universe<sup>12</sup>. Thus the assumption of many is that, in principal everything can be satisfactorily modelled as deterministic processes, except for a random residual – that is the world is neatly divided between the deterministic and the purely random. Certainly there are many that assert that almost all *macroscopic* events and processes are essentially deterministic<sup>13</sup>, in the sense that all relevant parts of the process can be satisfactorily represented as a deterministic process and the rest is not significant and so representable by random noise.

This picture coincides with the common modelling practice of using a pseudo-random source as a stand-in for an unmodelled residual, thus in the “noise traders” example above the unexplained “irrational” behaviour was modelled as random behaviour. This can be an appropriate approach if there is good reason to suppose that the residual *is* arbitrary to the modelled process so that the pattern of this residual does not make any significant difference to the model outcomes (which depends on the model use). A conflation of this modelling approach and a deterministic bias seems to lead some to the conviction that *any* unmodellable residual (a residual that is not capturable in a model in theory) *must be* random.

A particular case of such a conviction is that anything that is not deterministic *must be* random. That is the view that the world is divided between the random and the determined. In this view it may be that some things that appear random turn out to be merely very complex (i.e. we find a way to explicitly model the phenomena where we previously used a random/statistical proxy), and it may be that some things that appear deterministic are so only because of some grand “averaging out” of randomness at the detailed level (such as the atoms in a gas), but ultimately that is all there is: deterministic processes and random ones.

Such a view is closely related to the view that there are no essentially correct models that are necessarily context-dependent. That is to say, that it is always possible to reformulate a model to arbitrarily widen its scope – so that an essentially context-free model is possible. Given such an assumption it is always possible to claim that any unmodelled residual can be eliminated by expanding the model. A slightly weaker form of this assumption is that any *non-random* unmodelled residual is thus eliminable.

However if, on the other hand, some models are intrinsically context-dependent then this is far from necessary, the residual might not be modellable from within any appropriate context and the model might not be possible from within other (e.g. wider) contexts. Another way of putting this is that even the most appropriate context is not hermetically sealed, for there is inevitably some ‘interference’ from without. In this case the ‘interference’ might not be modellable but there is no reason to suppose that it *is best* ‘represented’ as a random term either<sup>14</sup>.

<sup>12</sup> Of course this does not convince convinced die-hard determinists who live in hope that quantum mechanics will be reduced to deterministic principles someday, as with Einstein’s famous quip “God does not play dice with the universe”.

<sup>13</sup> Despite the evidence from chaotic processes and models.

<sup>14</sup> Presumably the reason our cognition has divided the world into such contexts means that the amount of critical inter-contextual interference is minimal for its purposes, however the purposes of scientific

In many mundane cases it is clear that ‘noise’ does not have to be random. The noise of a bus in the street that is interfering with listening to a radio programme is not random just as the “ringing” of transistors after they have switched is not random. Neither are many chaotic systems random, as one can tell by an inspection of their mechanism, even if it is difficult to distinguish their outcomes from random outcomes<sup>15</sup>. As (Boffetta et al 2002) puts it:

*...the distinction between chaos and noise ... makes sense only in very peculiar cases, e.g., very low-dimensional systems*

One response of those who model electrical circuits to the inadequacy of modelling all electrical noise as “white noise” (that is noise which includes, at random, all frequencies) is to enrich the modelling of noise with properties other than the pure form of regulated randomness that characterises “white noise”. As Ritter (2003) put it:

*Both are fundamental sources of "white" noise, meaning that we have a deep statistical understanding of how these sources behave. Unfortunately, this may not be particularly useful if the noise we have is actually due to variable processing-related problems.*

Thus a variety of kinds of noise have now been developed, including “grey” and “black”. If it is right that noise is inherently context-dependent and not necessarily random then there will be no “new” kind of proxy for noise that will *always* be applicable. Determining what might be the most appropriate proxy for an unmodelled residual is an extremely difficult problem, one where it is difficult, *in principle*, to know what is most appropriate because this would require knowing something about modelling the unmodelled residual, which is not easily amenable to explicit modelling.

## **8. Conclusion**

Noise, in its more general usage can be usefully thought of as extra-contextual interference in what is being modelled. All effective modelling is context-dependent, and no context is completely “water tight” to influences from outside the context, influences that due to the nature of context are unmodellable. It is these influences that may interfere with the accuracy (and, indeed, applicability) of our model – we call these influences “noise”. We often model these influences with a random

modelling may be very different and this sort of pragmatic division of the world is heuristic in nature – it is not something that can be relied upon.

<sup>15</sup> This distinction between determining randomness via inspection of the mechanisms vs. by testing the outcomes is made clear in (L'Ecuyer 1992). This is interesting because it is precisely the aim of writing a random-number generating algorithm to separate the external and internal contexts w.r.t. to the generator – from the outside it looks random, whilst from the inside it is deterministic.

“proxy” because randomness is also unmodellable (in the sense of point-by-point detail).

Although many take randomness to be an essential property of noise, it should be clear from the analysis above that noise is not necessarily *random* but can be merely *arbitrary* with respect to the target. The confusion comes about because we use often randomness as an *archetypal model* for noise. Noise may be of almost any nature considered in isolation – it is only the poverty of our imagination that insists on casting it as its archetype.

## References

- Anderson, P.W. (1997) Some Thoughts About Distribution in Economics. In W. B. Arthur, S. N. Durlauf and D.A. Lane, (eds.) *The Economy as an Evolving Complex System II*. Reading, MA: Addison-Wesley, 566.
- Andersen, J. V. and Sornette, D. (2001) Have Your Cake and Eat It, Too: Increasing Returns While Lowering Large Risks! *Journal of Risk Finance*. **2**(3):70-82.
- ARUP (2001) The Millennium Bridge. ARUP's (the engineer's) site on the Millennium Bridge. <http://www.arup.com/millenniumbridge/> (accessed 15<sup>th</sup> May 2003).
- BBC News (2000) The Millennium Bridge. A BBC News report on the Millennium Bridge: [http://news.bbc.co.uk/hi/english/static/in\\_depth/uk/2000/millennium\\_bridge/](http://news.bbc.co.uk/hi/english/static/in_depth/uk/2000/millennium_bridge/) (accessed 15<sup>th</sup> May 2003).
- Black, F. (1986) Noise. *Journal of Finance*, **41**:529-43.
- Blake, W. J., Kaern, M., Cantor, C. R., Collins, J. J. (2003) Noise in eukaryotic gene expression. *Nature*, **422**(6932):633-637.
- Boffetta, G., Cencini, M., Falcioni, M. and Vulpiani, A. (2002) Predictability: a way to characterize complexity. *Physics Reports* **356**(6):367-474.
- Cartwright, N. (1983) *How the Laws of Physics Lie*. Oxford: Oxford University Press.
- Compagner, A. (1991). Definitions of Randomness. *American Journal of Physics*. **59**(8): 700-705. \*\*\*
- Delong, J. B., Shleifer, A., Summers, L., and Waldmann, R. J. (1990) Noise trader risk in financial markets, *Journal of Political Economy* **98**, 703-738.
- Dichev, I. (2001) News or noise? Estimating the noise in the US News university rankings, *Research In Higher Education*, **42**(3):237-266.
- Edmonds, B. (1999a) Modelling Bounded Rationality In Agent-Based Simulations using the Evolution of Mental Models. In Brenner, T. (ed.), *Computational Techniques for Modelling Learning in Economics*, Kluwer, 305-332.
- Edmonds, B. (1999b) The Pragmatic Roots of Context. CONTEXT'99, Trento, Italy, September 1999. *Lecture Notes in Artificial Intelligence*, **1688**:119-132.

- Einstein, A. (1905) Investigations on the Theory of Brownian Movement. *Annalen der Physik* 17:549-; (A.D. Cowper transl.), Methuen, London (1926) and Dover, New York (1956).
- Gupta, M. (Ed.) (1977) *Electrical Noise: Fundamentals and Sources*. IEEE Press. 51-58.
- Habermans, J. (1963) Theorie und Praxis. [Frankfurt am Main] : Suhrkamp Verlag. (English trans. Viertal, J. (1988) *Theory and practice*. Polity Press).
- Hesse, M. B. (1963). *Models and Analogies in Science*. London, Sheed and Ward.
- Hughes, R. G. (1997) Models and Representation. *Philosophy of Science*, **64**(proc), S325-S336. \*\*\*
- Kaneko, K. (1990). Globally Coupled Chaos Violates the Law of Large Numbers but not the Central Limit Theorem. *Physics Review Letters*, **65**: 1391-1394.
- Kolmogorov, A. (1965) Three Approaches to the Quantitative Definition of Information. *Problems of Information Transmission*. **1**:1-17. \*\*\*
- L'Ecuyer, P. (1992) Testing Random Number Generators. *Proceedings of the 1992 Winter Simulation Conference*. 305-313.
- Morariu, V. V., Coza, A., Chis, M. A. , Isvoran, A., Morariu, L. C. (2001) Scaling in cognition. *Fractals-Complex Geometry Patterns And Scaling In Nature And Society*, **9**(4):379-391. \*\*\*
- Peterson, I. (1997). Lava lamp randomness. *Science News* 152(Aug. 9):92. <http://www.sciencenews.org/20010512/mathtrek.asp>
- Pierce, J. (1956). Physical Sources of Noise. *Proc. IRE*. **44**:601-608. Reprinted in (Gupta 1977), 51-58.
- Ritter, T. (2003) Random Electrical Noise: A Literature Survey. <http://www.ciphersbyritter.com/RES/NOISE.HTM> (accessed 15<sup>th</sup> May 2003).
- Suppes, P. (1962) Models of Data. In Nagel, E; Suppes, P; Tarski, A (eds.). *Logic Methodology and the Philosophy of Science: Proceedings of the 1960 International Congress*. Stanford, CA: Stanford University Press, 252-261.
- van Kampen, N.G. (2001) Foreword: The Theory Of Noise. *Fluctuation and Noise Letters*, **1**(1):3-7.
- Wong H. (2003) Low-frequency noise study in electron devices: review and update. *Microelectronics Reliability*, **43**(4):585-599.