LETTER FROM THE PRESIDENT

Break out and embrace change

ENBIS
European Network for Business and Industrial Statistics
www.enbis.org

In his first letter as president of ENBIS, Fabrizio Ruggeri appeals to members to step outside their golden cages

Suppose a new by-pass road has been proposed in a city to decrease traffic passing through it. At the same time, its construction could be very expensive for the taxpayers and its impact on the environment could be devastating. Different stakeholders (inhabitants, industries, environmental groups, city counsellors) have different views; some aspects of the problem are stochastic (such as the traffic intensity) and a decision must be taken, considering the pros and the cons of the project.

You are probably thinking that the problem is relevant for the local community and challenging for the scientist (and you might come up with many others from your experience), but you might wonder why ENBIS should be involved in this. There is no 'usual' customer (an industry, say) with a 'usual' problem, such as the quality of its products. Where is the business? Who is the customer? Why should we bother? There are plenty of statisticians over there and they could take care of the problem!

I want to stress that we should not stay closed in our cages, even golden ones. We cannot think of the world and of our job as something where changes are only 'internal' to the system we have been used to: old customers, but with new products or, perhaps, with different management. There is a need for us, as statisticians involved in business and industrial problems, to look at society and its evolution and to seek new customers and new challenging problems. The by-pass road is an example of new customers and new problems. Here the customers are ourselves, as citizens, facing the problem of our participation in the decision process. This is democracy. Some of us have been working as consultants to public administrations (such as hospitals), but here I suggest we should go into a new business. We should think of citizens' groups as our customers, who have problems and need the methods we have been using and developing for many years.

When facing problems arising in local communities, ENBIS members and ENBIS Special Interest Groups (SIGs) can find plenty of work in looking at the data, formulating the problems, conducting the experiments, expressing preferences and beliefs, evaluating and comparing risks. Different skills are highly valued within ENBIS. Some of these are data mining, stochastic modelling, statistical consultancy and reliability and safety. These are names of a few of our SIGs. These skills can be thoroughly exploited in tackling the problems of local communities.

'We should think of citizens' groups as our customers, who have problems and need the methods we have been using and developing for many years'

I gave the example of citizens' groups and their problems as new customers. I could have spoken about, say, nanotechnologies and genomics, but I wanted a more provocative example. In one of his speeches at the ENBIS conference, Soren Bisgaard (past president and founder of ENBIS) mentioned 'innovation' as one of the key challenges of the future. I fully agree with him, provided we are able to understand the 'new' not only in our usual world, but also where the changes are more dramatic. ENBIS has created a network and a series of activities to be further expanded, like SIGs, advanced workshops (the first will be on data mining in Germany in Spring 2006), courses, the renewed and rich newsletter that will be on our website, the annual meeting with plenty of statisticians from companies and academia (the next one will be 18 to 20 September 2006 in Wroclaw, Poland) and all the other activities you will find on our website at www.enbis.org. ENBIS has a structure (and people, our best resource!) that will allow us to tackle new, challenging issues. Please, come and join us!

PS: My thoughts are based on my own experience. I am writing these notes just after my return from Manchester (UK), where I attended a workshop organised by the European Science Foundation programme 'Towards Electronic Democracy: Internet-based Complex Decision Support (TED)', in which I am deeply involved. See www.esf.org/ted for more details on the approach I have briefly mentioned here. The project involves statisticians and decision analysts who are exploring how their methods can be used in a world in which the development of the World Wide Web allows many people to access plenty of information and discuss problems at local and global level. Statistical methods have been used, for example, in comparing opinions of stakeholders and developing tools for getting widely-agreed decisions through some processes, like e-negotiation and e-arbitration.

More about reliable systems for trains

Elizabeth Viles and David Puente recently described (March/April 2005) how they helped to improve maintenance of an electronic communications and control system for trains. Their colleagues, Maria Jesús Alvarez and Laura Ilzarbe, joined them to improve the reliability and robustness of the system using a Six Sigma approach

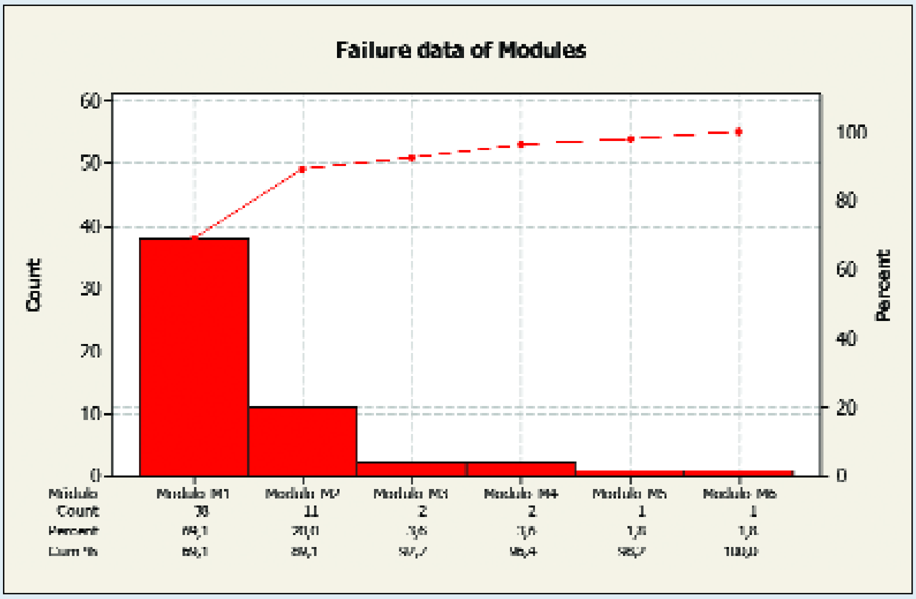

Figure 1: Pareto chart of number of failures.

In a previous article, we described an approach to the railway sector and the communications problem. In that study, we resolved some of the problems related to the reliability, especially the maintenance, of this system. After that, the company asked us to take a further study in order to improve the quality and reliability levels achieved previously. So, we decided to introduce the Six Sigma approach.

Six Sigma is a powerful business strategy that employs a well-structured methodology to improve the quality of a product or a process using effective application of statistical tools and techniques. This methodology is known as DMAIC cycle (Define, Measure, Analyse, Improve, Control), and has brought significant benefits to many organisations.

This work is part of a bigger research project that Tecnun and a railway sector company is carrying out in order to improve the reliability and robustness of a complex electronic communication system for trains. We have a confidentiality agreement, so we have changed the names of the system and its components.

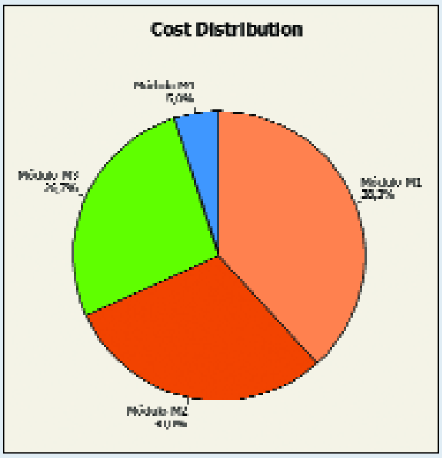

Figure 2: Warranty costs data of these failures.

The company first wanted to describe the reliability of its electronic communication system for trains. The enterprise was new and the system was being used for the first fleet of trains. The system is complex, with several modules, cards and other electronic elements. In a previous study, we had shown that one module of this system was more critical than the others. Figures 1 and 2 show that 69 per cent of the failures registered from the first fleet of trains containing the system came from 'M1 module' and this caused 38 per cent of total warranty costs.

The Six Sigma Team focused on improving the reliability and robustness of 'M1 module'. The company set the following goals:

- Improve the reliability of this module eight times;
- Make a module more robust to electrical and environmental stresses; and
- Reduce the manufacturing costs by about 30 per cent.

In the Define stage we defined the boundaries of this project (manufacture and assembly process of 'M1 module') and we thought about how to measure the CQT (critical to quality characteristics) of this process. We used as response variables: the numbers of failures per hour of different components of 'M1 module'; their technical properties; and their costs.

In the Measure stage the big problem was the lack of data. Luckily, we had data about the failures in the system (a failure in this system could mean a train is out of order). However, this was not a new situation for us because, in a previous study, we had seen that the theoretical data using norms produced the same critical elements as the real data. This is one reason why we thought that the use of these norms to find the critical elements of this module would help us to resolve this problem.

We first compared the real data about the reliability of the cards contained in 'M1 module' with the theoretical reliability data using MIL-HNBK-217 F norm. As we can see in Figures 3 and 4, after checking that card 4 had design problems, we realised that two of the cards included in 'M1 module' were critical for its functionality.

Therefore, following the same reasoning, in the Analyse stage we analysed the theoretical reliability data of the components of the previous cards to detect the most critical components in 'M1 module'. Before analysing various charts we focused our study on three components whose contribution to the overall reliability of the system was around 60 per cent.

At present, the company is not the owner of the circuit design of 'M1 module'. For this reason, in the Improve stage, we suggested to the management two possible work lines. One of them was to find more reliable and robust components in the market for the critical components identified in that study. The second was that they themselves should design a new 'M1 module'. After considering the advantages and disadvantages of these two alternatives, the company management decided to take the following steps: in the short term, study improvements for the critical components, and in the long term, design a new 'M1 module' for the communication system, including the improvements achieved earlier if possible.

We have found different solutions to improve the reliability of the previous components (such as changing the provider, a derating of five per cent or making some components redundant). Merging different possibilities, it is possible to reduce the failure rate by around 24 per cent, at practically the same price. But the company management has considered the design as a priority and, now, we are following the stages of DFSS (Design For Six Sigma) methodology to achieve the best design of 'M1 module'.

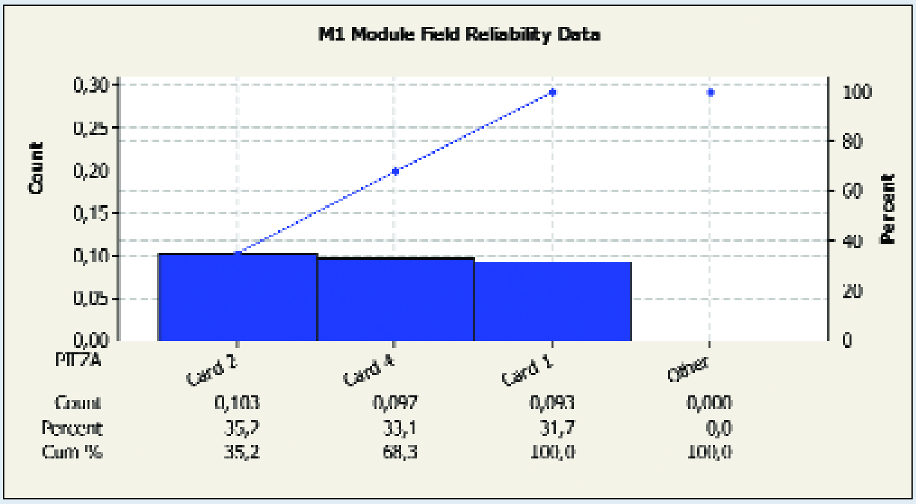

Figure 3: Real data from 'M1 module'.

	Find more reliable and robust components	Develop a new design
Reliability improvement	Moderate (limited to the design)	Very high (design for reliability)
Necessary time to introduce improvements	Short term	Long term
Improvement areas	Reliability and robustness	Reliability, robustness, design, test, production, ease of maintenance
Investment	Very low	Very high

Figure 5: Advantages and disadvantages of possible improvement actions.

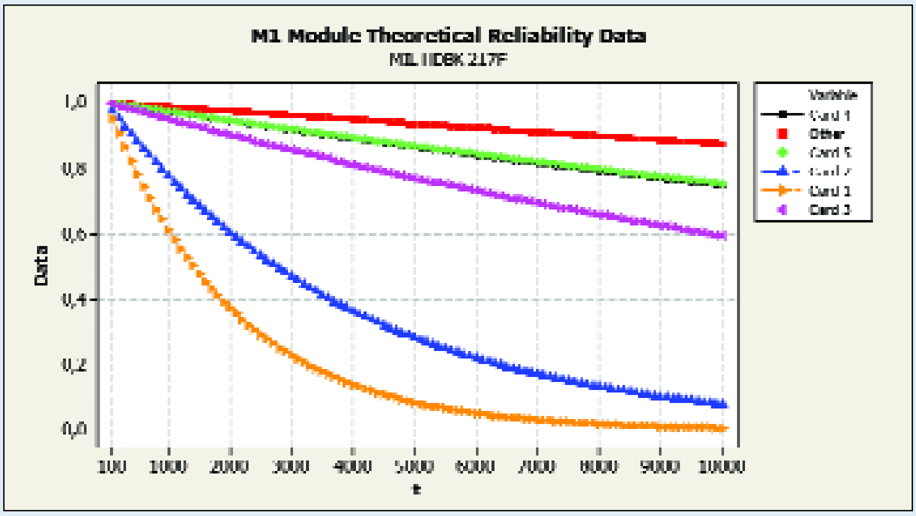

Figure 4: Theoretical reliability data for 'M1 module'.

Acknowledgements

This study has been partially supported by a grant from the Department of Education, University and Research of the Basque Country Government, under the project UE2004-4.

The authors are at the Department of Management Science of Tecnun (University of Navarra). The department's scope includes management, quality, information technologies and human resources and it develops several research projects and collaborates with companies. It also belongs to the Cathedra of Quality 'University of Navarra-Volkswagen'.

Statistics unravelled

John Logsdon discusses maximum likelihood and shows how it can be used, with the Weibull distribution, to predict a one per cent time to failure

'In all likelihood we will freeze this winter,' the met man said. Politicians, bookmakers, even scientists, talk about likelihood. But what is it?

The Oxford English Dictionary defines likelihood as: 'noun: the state or fact of being likely', which doesn't seem too helpful. Likelihood is commonly used to express the most probable of outcomes. The bookies' favourite in the 2.30 at Doncaster is the horse that they think is most likely to win – or rather it's the horse on which the bookies are likely to lose most money if it wins, and that depends on the perception of the punters. So they shorten the odds. We would say that the horse will win in all likelihood.

Likelihood is a measure of probability. Statisticians use the word more formally to mean the probability of several events happening at the same time. That's a bit loose, but it will do for the moment. The important point is that likelihood is a probability. Unlike the common use, likelihood in statistics does not imply the most likely outcome; we use 'maximum likelihood' for that.

Maximum likelihood – or ML – is a powerful tool for 'fitting' the model to the data. Notice the emphasis: the data is correct, but the model contains unknown parameters that need calibrating. Likelihood is therefore a function of the parameters in a model, given the data, and this makes maximisation tractable – either by algebra or standard optimisation algorithms. It is not too big a claim to suggest that maximum likelihood is the bedrock of statistical modelling. There are other approaches, but it is the most commonly used and best understood way of '*fitting the model to the data*'.

Let's consider an example. Suppose you have a set of measurements of time to failure. It may be bearing failures, rupture of a tube, or failure of an electronic product. Let us assume that we only have five measurements and the management believes you are a magician. They want to know how long to expect the product to last before one per cent have failed so that they can escape before all the product warranty claims arrive. We put aside the ethics of answering such a question!

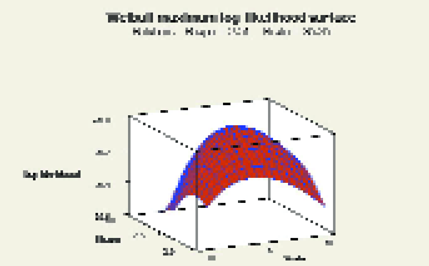

Figure 1

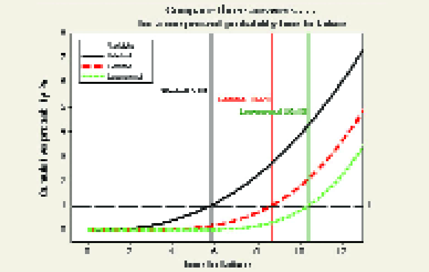

Figure 2

The data are: 17, 54, 29, 19 and 41 hours, days, years or whatever. You have been doing some thinking and calculate a mean of 32 and a standard deviation of 15.6. For a normal distribution, the one per cent value is -4.2. Oh dear.

So you take logs and come up with 9.2. There is much confusion about using logs. What justification do you have for taking logs, other than ensuring the answer is positive? Welcome to the statistical world.

But there is a way, and you remember reading something in the literature that the Weibull distribution is often used for assessment of time to failure. To fit this new model to the data, you call on your new ML friend and calculate the time by which you estimate one per cent would have failed. This works out at about 5.8 and you march into the MD's office, confident of your answer.

To show the MD what you have done, you have prepared a likelihood plot, as in Figure 1, using the R statistical and graphics program. Because there are two parameters, you show it as a perspective plot and pray that he is not confused. The *z*-axis is the log-likelihood, which is a measure of the probability of the data you have – those famous five points – coming from the assumed model, the Weibull distribution. The other two axes are of parameters in the Weibull distribution that represent its scale and its shape. Note that, in this case, the graph is really quite flat because you have so little data. The axes are chosen to exaggerate the curvature.

You acknowledge that your answer may be wrong, but then statistics is the art of being least wrong with justification. We call statistics the science of uncertainty.

What if it is not a Weibull distribution? After all, there are only five points and you would need many more to be reasonably sure. Figure 2 shows the left-hand part of three distributions fitted to the same data: the Weibull, the Gamma, and the Log-normal. The graphs are the cumulative probabilities based on the data. We show the one per cent value for each of the distributions. That is what the management has asked you: What is the time after which there is a greater than one per cent chance of failure?

There is a lot of difference between the answers. But you are clever enough to have done some further sums that show that you will get a better answer with a lot more data. Whatever the distribution, the uncertainty both in distribution and the one percentile estimate would be much smaller and so your answers can be more precise and hopefully accurate.

Only by using maximum likelihood can you do such calculations or draw such inferences. Least squares, the usual approach taught at university, cannot compare distributions because, at best, it implies a normal distribution. This may be entirely appropriate in some situations. Tasks such as fitting straight lines with a normal distribution will give the same answer either by maximum likelihood or least squares. And important tools such as the analysis of variance are intimately connected with least squares.

But to investigate distributions, more complex effects and in particular the behaviour of the extreme values – largest or smallest – you need to start with maximum likelihood.

The happy ending is that the management are so impressed with your new fluency that they accept the case for more tests – and send you on a statistics course. In the next issue we will deal with more aspects of likelihood estimation.

The coding that produces the answers can be found at **www.enbis.org/SCW2.R**. You can play with the number of values generated but remember to change the plotting ranges to suit.