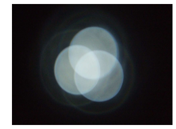
Issue 6.1 March 2009

Nosokinetics News

Quarterly Newsletter of the UK Nosokinetics Group
Past issues at http://www.nosokinetics.org/



Contents

Congratulations to Revlin Abbi PhD, from Elia ElDarzi's group at Harrow Campus of University of Westminster. His doctoral thesis 'A patient length of stay grouping and predicting methodology incorporating Gaussian Mixture models and Classification algorithms' breaks new ground and gives remarkable insights into the process of care. The thesis was co-supervised by Christos Vasilakis.

The brilliance of Revlin's contribution, describes a novel clustering approach to separate out clinically meaningful groups in large data sets. Moreover, his approach enabled Prof Malcolm Faddy to describe four components, made up of several phases in the same data. See Readers write, page 6, for a letter from Malcolm pointing out the difference between components and phases. And pages 2 and 3 where Revlin describes the clinical relevance and practical potential of the new methodology using length of stay data for over a hundred thousand stroke patient data in the English National HES data set.

There is an interesting relationship between the advent of the computer era, chaos in banking and bed crises in hospitals. Sally would instantly reply, "Correlation is not causation", and I agree. Let me explain, however, why, in both fields of endeavour, I think that misunderstanding of the use and abuse of computer generated 'numbers' is the root cause of current difficulties in both sectors.

Both are human activity systems and in both beds and shares there are movers and stayers. Before the computer era, paper transactions were used in the Stock Exchange to buy and sell shares; similarly, manually collected midnight bed states and admission books underpinned performance comparison in hospitals.

Now algorithmic trading or automated trading, also known as algo trading, black-box trading, or robo trading (Wikepedia) is used in financial markets. Nearly fifty percent of trades are now done by computers. Look at the daily pattern of share dealing. The speed of rise and fall clearly shows a herd generated chaotic system, driven down or up by computers generated numbers. Whereas, the reality is that most shareholders are not selling, and if people knew who was gambling, would everyone panic.

Similarly, forty years after the dawn of the computer era changed the way that throughput in hospitals was measured, hospitals are in chaos. Is it cause and effect - I think so. Its twenty years since both Gary Harrison developed a mathematical two compartment model to explain the exponential nature of flow in midnight bed states. And Sally McClean began her research into the phases of care in cohort data sets. Now 11 doctoral theses and over 100 papers later the SCIENCE BASE OF NOSOKINETICS IS CLEAR — What next?

Portrush 2008: Post Conference Publication

Intelligent Patient Management

Series: Studies in Computational Intelligence, Vol. 189
McClean, S.; Millard, P.; El-Darzi, E.; Nugent, C.D. (Eds.)
2009, Approx. 350 p., Hardcover ISBN: 978-3-642-00178-9
Online version available at http://springerlink.com/content/119788/
Due: March 2009 £112.50

For Engineers, researchers, and graduate students in computational intelligence, computer science and health care

Arguably medicine is either an arts-based science or a science-based art. In medieval times, clinical decisions were based on simple measures, such as the temperature of the body, the rhythm of the pulse, the consistency of the stool and the colour of the urine. Nowadays, thanks partly to modern technology, medical science has improved in many ways, as has healthcare. In particular, approaches which have their origins in Artificial Intelligence and Operational Research have a significant contribution to make in terms of improving not only diagnosis and treatment of patients, but also providing ways of managing patients in a more effective, more efficient, and more patient-friendly manner. This book focuses on the use of such Intelligent Patient Management to the benefit of patients, clinicians and other health workers.

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Data mining health administrative and patient length of stay data for better understanding of patient populations and for making predictions of likely length of stay upon patient admissions by **Dr Revlin Abbi** (comments to revlin@gmail.com)

Editor's comment: Revlin's computational research in Elia ElDarzi's group at Harrow campus of Westminster University opened my eyes. His PhD research into length of stay groupings in large data sets, shows what can and, I may say, should be done, to transform understanding of the impact of complexity on length of stay and the place of complexity in illness management. Here focusing on stroke illness he reveals the interaction of degrees of difficulty on need, outcome and resource use.

Introduction: Improving the planning and management of health care is crucial if health services are to respond effectively to increasing demands from demographic pressures and budgetary constraints. Current approaches for planning and management are often deemed too simple and insufficient, primarily because they overlook the heterogeneous nature of patient populations and their implications on the overall system.

Method: We put forward a grouping and classification methodology, specifically designed to identify clinically meaningful homogeneous groups of patients within a diverse patient population. Furthermore, the methodology is capable of predicting the LOS of any one particular patient based on their available spell and/or patient characteristics. Essentially two types of information are derived from this approach.

The first type of information is related to a grouping model extracted from patient length of stay (LOS) data. This information would enable health care professionals to estimate the number of groups within a given population and for each group, the likely proportion of patients; the likely resource consumption including workload, the number of beds required, as well as the average LOS of patients. These group statistics can be used instead of overall population statistics such as the simple average LOS of a population. The second type of information relates to the prediction of patient LOS based on various spell and/or patient characteristics (also see June 2007 Issue 4.3 of Nosokinetics News).

Modelling stroke illness: Table 1 shows the outcome of applying the methodology to a Stroke data set. In this case, the methodology suggests that the stroke population consists of five groups.

Table 1: Group statistics for 103,846, first admission, stroke patients discharged from English Hospitals between April 1st 1994 and March 31st 1995

Group parameters	Patient group				
	1st	2nd	3rd	4th	5th
Mean (days)	1.0	5.6	14.5	41.5	339.7
Standard Dev. (days)	0.0	2.6	6.2	22.2	520.4
Proportion (%)	12.3	37.8	36.7	12.6	0.7
Workload (%)	0.8	14.0	35.1	34.5	15.7

Five groups: The first group represents 12.3% of the population who stay in hospital for one day. The second represents 37.8% who stay on average 5.6 days with a standard deviation (SD) of 2.6 days. The third group represents 36.7% who stay on average 14.5 days with a SD of 6.2 days. The fourth group represents 12.6% who stay on average 41.5 days with a SD of 22.2 days. Lastly, the fifth group, i.e. the long stay patients, represents 0.7% of the population who stay in hospital on average for 339.7 days with a SD of 520.4 days.

Clinical relevance: The groups derived by the methodology directly correspond to clinically meaningful patterns of stroke patient recovery as described by (Harwood R et al., 2005). The first pattern of recovery is Transient Ischaemic Attack (known as TIA) a minor, non-disabling stroke, which lasts less than 24 hours. The second is a mildly disabling stroke, where the patient recovers to independence within a week or two. The third and fourth stages represent moderate or severe stroke illness requiring many weeks of rehabilitation to reach maximum abilities. Lastly, the fifth pattern represents severely disabled people whose medical and social circumstances required long term care and whose discharge is usually by death.

Workload: The group statistics can also be used to calculate the workload in bed days, presented as a percentage for each group in relation to the overall work load. From table 1, the first group—12.3% of discharged patients with a mean LOS of one day - account for less than one percent of the admitted patients as expressed in bed-days. *(continued overleaf p5)*

In other words, the short stay group, one eighth of the population, account for only one-hundredth of the daily bed use. Based on this information, groups three and four represent the majority of the workload.

Bed usage: Estimating bed Furthermore, based on a static number of admissions (e.g. minimum, average or maximum number of admissions) and the group parameters, the methodology can determine the number of beds required for the population as well as for each group. For example in Table 2 we take the minimum number of admissions as 269 patients per day, the average as 282 and the maximum number as 301, then the national minimum, average and maximum number of beds required is 4,304, 4,511, and 4,816 beds respectively. Also, if required, these bed requirement statistics can be broken down according to each group, e.g. the number of beds required for patient group five, the long stay group of patients, would be a minimum of 774 beds, an average of 811 beds, and a maximum number of 866 beds.

Table 2: Estimated number of beds required for 103,846 first admission Stroke patients

Patient group	Admissions (per day)			Number of beds		
	Min (269)	Avg (282)	Max (301)	Min	Avg	Max
1	33	35	37	50	52	56
2	102	107	114	620	650	694
3	99	104	110	1,473	1,544	1,648
4	33	35	38	1,420	1,489	1,589
5	2	2	2	774	811	866
Total	269	282	301	4,304	4,511	4,816

What if?: Once the grouping model is derived using our software, the mathematics involved can be embedded into a simple spreadsheet package such as Microsoft Excel and can then be used to help make more informed decisions with respect to changes in management strategies, staff behaviour or allocation, policy changes, etc. For example, we may perform a what-if analysis to seek answers to the following questions:

1. 'If we spend more time and effort on a particular group, thereby, reducing this group's average LOS, what would be the overall outcome on the bed requirement for the hospital?' We may also answer questions relating to individual patients such as:
2. 'Given that a particular patient has been in hospital for *d* days, what is the probability that the patient belongs to group *j*? and/or
3. Given that a particular patient belongs to group *j* and has already been in hospital for *d* days, how many more days is this patient expected to remain in hospital?

Prediction: A decision tree classification model is used to make predictions for particular patients on their likely LOS. The tree is developed using the same set of administrative data from which the LOS data was derived; however in this case, the methodology considers the relationship between the groups defined in the grouping model with variables within the data such as diagnosis, admission source or method, age, gender, etc. The outcome of this procedure is a tree model that is essentially a graphical representation of a set of rules that can be used to make predictions for future patient admissions, e.g. if diagnosis = *x* AND age = *y* AND admission method = *i*, then LOS=10-28 days. One shortfall of this approach is that the prediction accuracy for the long stay patients is very low compared with the accuracy for the short stay patients. To overcome this, the methodology performs a sensitivity analysis whereby the tree model is refined to increase the accuracy for the long stay patients.

Conclusion: In summary, the PhD research outlined in this article shows that the methodology is capable of autonomously adjusting the number of groups and model parameters according to the LOS data used. The derived grouping model accurately fits skewed data and is robust against outliers. The approach can be used to make comparisons of the LOS of different health facilities and hospitals. This has been illustrated when comparing the LOS of patients between fourteen different regions. Moreover, it can be used to predict the LOS of admitted patients based on various characteristics and ensures that higher prediction accuracy is achieved for long stay patients.

References: Harwood R., Huwez F. and Good D. (2005) *Stroke Care: a practical manual, trajectories of recovery (page 60)*, Oxford University Press.

Issue 6.1

Nosokinetics News

March 2009

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Dynamics or Statics — Which way forward?

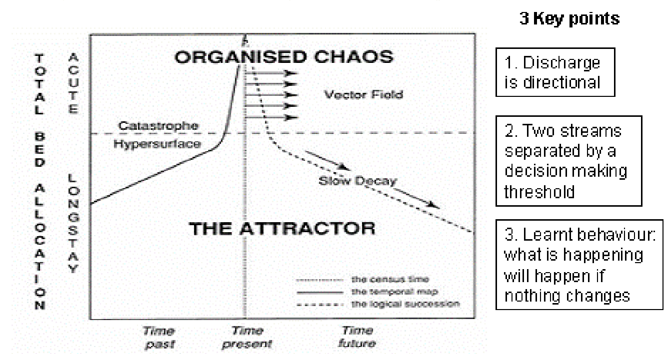
Our garden: snowed man artefact

What a strange world we live in. Global warming! Forest fires in Australia; Deep Snow in UK. Now too, economically the chickens are coming home to roost. Early on in our research into the exponential nature of the flow of patients through departments of geriatric medicine, discussing the problem with two Senior Lecturers in Biochemistry, I was reliably informed that the linear equations used in Marshal's textbook of economics underpin the equations used in biochemistry.

When, in 1989, I first met Gary Harrison, in Charleston, he lent me a book on calculus to see if I could find an analogy for the process model in my 1989 thesis Figure 1 (now on web at http://www.nosokinetics.org/).

The chosen model was of a plant leaf creating chlorophyll. However, a more clinically relevant, equivalent ,mover/stayer process, is the impact of sunlight on the manufacture of Vitamin D. Ultraviolet light striking human skin sets up a biochemical process which manufactures Vitamin D. The Vitamin necessary, among other things, for muscle strength, immune processes and strong bones.

A theoretical, biological, model of the process of inpatient care in a department of geriatric medicine



Adapted from Thom (1975): Millard MD thesis 1989

The process only lasts for twenty to thirty minutes, thereafter, however long we remain in the sun, we get sunburnt, but we don't get anymore Vitamin D, until the next time we go out, when the process begins again. In the UK, this process only occurs between May and September, because in the other months the angle of the earth to the sun filters out the necessary ultraviolet rays.

Luckily, metaphorically, looking forward to rainy days, extra Vitamin D made in Summer months is stored in the muscles and there is a recycling mechanism in the small intestine which reabsorbs most of the Vitamin D excreted by the liver. Biologically, this relationship between sunshine and sunburn probably explains why white skinned people live at Northern Latitudes and black skinned at the equator, as in both areas there is an edge for survival. White, because Vitamin D deficiency causes childhood rickets which makes the pelvis smaller and birth more difficult. And Black because of the strength of the sun.

Which brings me back to our cause. Mathematics is a language with strict rules, whose practical implications are subordinate to the process of care recognising. The biochemical equation

$$Ac - Rd = Lv$$

is easy to write in symbols, but much harder still to achieve. For the equation reflects three things.

1. Ac reflects the relationship between the occupied acute medical beds and the locally prevailing staff learnt behaviour with regard to referral to long term care. "We've always done it this way, why should we change?"
2. Rv reflects the need to create a hospital based, community supportive service, which enables potential long term patients to be managed elsewhere. As, using the words of Boucher (1954), they are 'inpatients with sleeping out passes' and their needs and the needs of their supporting networks cannot be ignored. Moreover discharged patients come back.
3. The need to recognise that small numbers of increased admissions to long term care make big differences. Given a half-life of eighteen months in long term care, one in twelve admitted residents will still be alive six years after being admitted

Box 1

Ac reflects the number of inpatients in the hospitals being processed for long term care.

Rd equals the number being rehabilitated for community support

Lv describes the rate of discharge from occupied long term beds, usually by death, i.e *v is the death rate*.

(continued page 5)

Looking back to 1968, when we began to create a new style of practice in the geriatric medical service serving the London Borough of Merton, the waiting list was 68. In 1969, there were 186 beds and 437 admissions, i.e. 2.4 per allocated bed with an average stay of 155 days. Eight years later, 969 patients were admitted to 181 beds, i.e. a turnover per bed of 5.4 patients with a service time of 68 days. 1: 25 of the 25,000 over 65's in the Borough of Merton had been or were inpatients.

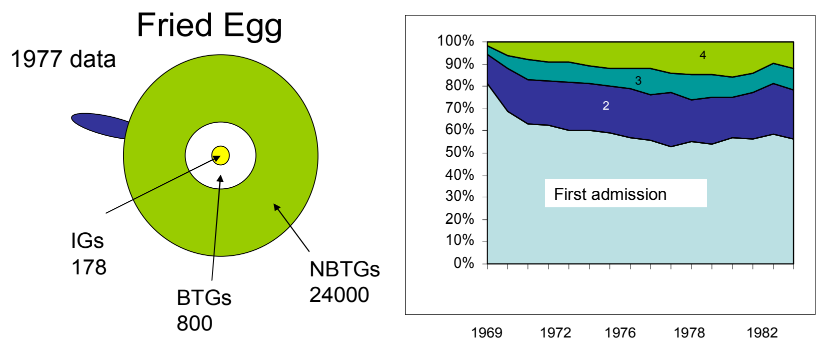
Think of the relationship between rehabilitation and enablement as a means of control of long term numbers, as an egg in a frying pan.

The frying pan is the Merton catchments area, with 25,000 residents aged 65 and over. In 1977, 24,000 had not been inpatients (NBTGs). The yolk contains 178 inpatients (IGs) and the white represents 800 residents who have in that year or previous years been inpatients in the department of geriatrics BTGs.

Note too, from the histogram, how in the early years of the departments development the number of patients being admitted two, three and four time increased. Such that by 1997, and thereafter, 45% of admissions were of patients already known to the department. Which, given that the patients are admitted to the same department is not a large workload.

Discharged patients come back

1969-1984 St. George's Geriatrics

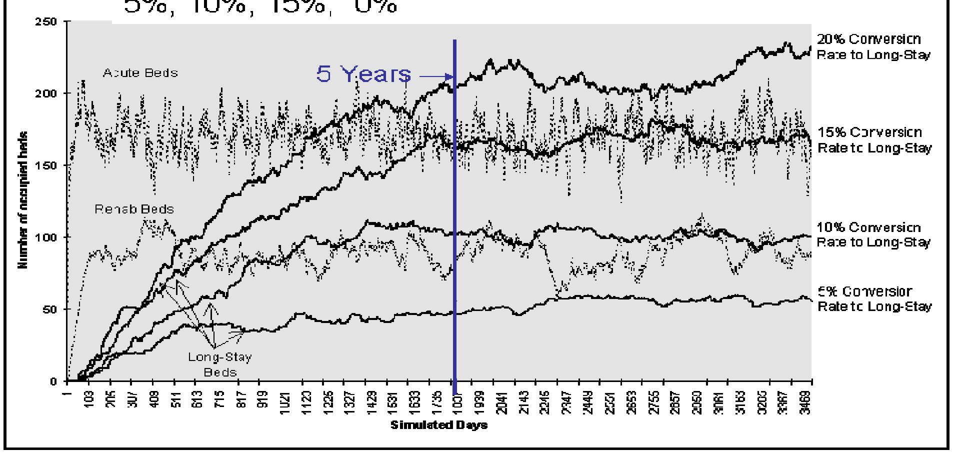


Day care, respite care, holiday admissions, and 24 hour available hospital beds admission to maintain trust between the patient, their family, neighbours and friends.

NB: IGs in geriatrics: BTGs been to geriatrics; NBTG's not been to geriatrics

Referring back to Ac - Rd = Lv. The simulation model, using data from a North London Geriatric medicine, shows that five to six years must pass before the outcome of change in clinical systems providing acute, rehabilitation and long-stay services can be judged.

Geriatric Medicine: Time to stable state and beds needed for four different conversion rates to long stay: 5%, 10%, 15%, "0%



El-Darzi, E., C. Vasilakis, et al. (1998). A simulation modelling approach to evaluating length of stay, occupancy, emptiness and bed blocking in a hospital geriatric department. *Health Care Management Sciences* 1(2): 143-9.

READERS WRITE

Malcolm Faddy writes: Components not phases. What's in a word? Everything

First, happy new year! Thanks for putting that piece in last December's Nosokinetics News about my phase-type fit to those stroke patient length of hospital stay data. I hope you won't mind if I make a couple of points. Strictly speaking, there were four components, not phases, to the fit (technically, each component is made up several phases) - we mathematicians/statisticians are a little fussy about notation!

The other point is that I suspect that the fourth component would very likely accommodate those patients you describes as "long stay" as the exponential tail of this component is very long - much longer than the tail of a normal distribution. I'll have a look at the largest observations in relation to this tail, and maybe also describe the four components in terms of medians and quartiles, rather than mean and standard deviation, to exemplify the tail lengths.

I trust that you are well, and that the extreme weather in England is not too trying. We seem to be sandwiched between two extremes - extensive flooding to the north and terrible bushfires to the south. Although it has been very hot, necessitating much use of air conditioning!

With best wishes,

Malcolm

Prof Malcolm Faddy, Brisbane

Twenty Years: Eleven Doctoral Theses Since 1989

Millard, Peter H. (1989) *Geriatric medicine: a new method of measuring bed usage and a theory for planning. Medicine,* University of London. **MD**. http://info200.infc.ulst.ac.uk/nosokinetics/pdf/PHM_1998_MD_master5.pdf

Millard, Peter H. (1993) *Flow rate modelling: a method of comparing performance in departments of geriatric medicine,* University of London. **PhD**. http://info200.infc.ulst.ac.uk/nosokinetics/pdf/PhD.Thesis.-.Millard.1992.pdf

Taylor, Gordon J. (1997) *Geriatric flow rate modelling*. Faculty of Informatics, University of Ulster. **PhD**.

Marshall, Adele (2001) *Bayesian belief networks using conditional phase-type distributions*. Faculty of Informatics, University of Ulster. **PhD**.

Vasilakis, Christos (2003) *Simulating the flow of patients: an OLAP-enabled decision support framework*. University of Westminster. **PhD**.

Xie, Haifeng (2004) *Modelling issues in institutional long-term care: placement, survival and cost*. University of Westminster. **PhD**.

Shaw, Barry (2006) *An extended Bayesian network approach to model the health care costs of patient spells in hospital*. Queen's University, Belfast. **PhD**.

Patel, Brijesh (2007) *Performance and the National Health Service: modelling for formative policy evaluation and strategic planning*. University of Westminster. **PhD**.

Mackay, Mark (2007) *Compartmental flow modelling of acute care hospital bed occupancy for strategic decision making*. School of Psychology, University of Adelaide. **PhD**. http://digital.library.adelaide.edu.au/dspace/bitstream/2440/41204/1/02whole.pdf

Demir, Eerin (2008) *Modelling readmission: defining and developing a framework for profiling hospitals*. University of Westminster. **PhD**.

Abbi, Revlin (2009) *A patient length of stay grouping and predicting methodology incorporating Gaussian Mixture models and classification algorithms*, University of Westminster. **PhD**.

POT POURRI: 18 papers

.Barabasi, A. L. (2005). "The origin of bursts and heavy tails in human dynamics." Nature .**435**(7039): 207-11.
There is increasing evidence that the bursty nature of human behaviour is a consequence of a decision-based queuing process: when individuals execute tasks based on some perceived priority, with most tasks being rapidly executed, whereas a few experience very long waiting times. These finding have important implications, ranging from resource management to service allocation, in both communications and retail.

Barnett, A. and N. Graves (2008). "Competing risks models and time-dependent covariates." Crit Care **12**(2): 134.
Competing risks models and multistate models offer significant advantages over standard survival analyses. A competing risks model to examine survival times for nosocomial pneumonia and mortality incorporate time-dependent covariates shows how risk factors that changed with time affected the chances of infection or death. An alternative modelling technique (using logistic regression) can more fully exploit time-dependent covariates for this type of data.

Bayat, S., M. Cuggia, et al. (2008). "Modelling access to renal transplantation waiting list in a French healthcare network using a Bayesian method." Stud Health Technol Inform **136**: 605-10.
The probability of registration is associated to age, cardiovascular disease, diabetes, serum albumin level, respiratory disease, physical impairment, follow-up in the department performing transplantation and past history of malignancy. Data mining enables a global view of the variables' associations. These approaches constitute an essential step toward a decisional information system for healthcare networks.

Beyersmann, J. and M. Schumacher (2008). "Time-dependent covariates in the proportional subdistribution hazards model for competing risks." Biostatistics **9**(4): 765-76.
Uses the intimate relationship of discrete covariates and multistate models to naturally treat time-dependent covariates within the subdistribution hazards framework. The methodology is illustrated with hospital infection data, where time-dependent covariates and competing risks are essential to the subject research question.

Constantinides, V. A., P. P. Tekkis, et al. (2006). "Fast-track failure after cardiac surgery: development of a prediction model." Crit Care Med **34**(12): 2875-82.
Multifactorial logistic regression was used to develop a propensity score for estimating the likelihood of fast-track failure. One hundred and sixty-nine patients (15.6%)failed fast-track management. The fast-track failure score incorporates several preoperative factors.

Crombie, A., J. Ham, et al. (2008). "Planning for transition care." Aust Health Rev **32**(3): 505-8.
Case study "How many places should be allocated to transition care in our facility?" This case study offers an approach to this question based on queueing theory.

Demir, E., T. J. Chaussalet, et al. (2008). "Emergency readmission criterion: a technique for determining the emergency readmission time window." IEEE Trans Inf Technol Biomed **12**(5): 644-9.
Readmission of discharged patients can be broadly divided in to high risk and low risk groups. Using English national data probabilities of being in the high-risk group for COPD, stroke, and CHF patients and for each of the 29 acute and specialist trusts in the London area indicate wide variability between hospitals. Provides a unique approach in examining variability between hospitals, and potentially contribute to a better definition of readmission as a performance indicator.

Desai, M. S., M. L. Penn, et al. (2008). "Modelling of Hampshire Adult Services--gearing up for future demands." Health Care Manag Sci **11**(2): 167-76.
Uses system dynamics to explore the significant challenges of an ageing population in the context of budget limitations.As anticipated, the numbers requiring care will increase considerably over the next 5 years. The effects of two possible interventions to reduce the impact of this are explored.

Gallivan, S. (2008). "Challenging the role of calibration, validation and sensitivity analysis in relation to models of health care processes." Health Care Manag Sci **11**(2): 208-13.
The discussion challenges the view that modelling should necessarily be subject to formulaic calibration, validation and sensitivity analysis processes in an attempt to achieve or establish 'accuracy'. If calibration and sensitivity analysis are to be carried out, there is a need to be clear about what the objective is in such analyses.

Kinsman, L., R. Champion, et al. (2008). "Assessing the impact of streaming in a regional emergency department." Emerg Med Australas **20**(3): 221-7.
A streaming model had an impact on the two performance indicators associated with length of stay in this regional ED, but did not have a significant impact (positive or negative) on the percentage of patients who did not wait to be seen.

Masters, S., J. Halbert, et al. (2008). "What are the first quality reports from the Transition Care Program in Australia telling us?" Australas J Ageing **27**(2): 97-102.
Transition Care offers older people a flexible model of care. While the flexibility of the model is a strength, service providers are struggling to achieve integration with existing services.

Patrick, J. and M. L. Puterman (2008). "Reducing wait times through operations research: optimizing the use of surge capacity." Healthc Q **11**(3): 77-83.
Provides a case study of the use of several OR methods, including Markov decision processes, linear programming and simulation, to optimize the scheduling of patients with multiple priorities. Wait time targets can be attained with the judicious use of surge capacity in the form of overtime.

Shahani, A. K., S. A. Ridley, et al. (2008). "Modelling patient flows as an aid to decision making for critical care capacities and organisation." Anaesthesia **63**(10): 1074-80.
Using real data a tuned model which accurately reflected the base case of the flow of patients was used to predict alterations in service provision in a number of several scenarios. The model takes variability and uncertainty properly into account and it provides the necessary information for making better decisions about critical care capacity and organisation.

Sharma, R., M. Stano, et al. (2008). "Short-term fluctuations in hospital demand: implications for admission, discharge, and discriminatory behavior." Rand J Econ **39**(2): 586-606.
On high-demand days, patients are discharged earlier than expected. High demand creates no statistically significant differences in admission behavior. Thus, capacity by hastening discharges rather than by restricting admissions.

Shwartz, M., J. Ren, et al. (2008). "Estimating a composite measure of hospital quality from the Hospital Compare database: differences when using a Bayesian hierarchical latent variable model versus denominator-based weights." Med Care **46**(8): 778-85.
Both conceptually and practically, hospital-specific DBWs are a reasonable approach for calculating a composite measure. However, this approach fails to take into account differences in the reliability of estimates from hospitals of different sizes, a big advantage of the Bayesian models.

Siciliani, L. (2008). "A note on the dynamic interaction between waiting times and waiting lists." Health Econ **17**(5): 639-47.
Develops a stylised model: predicts the dynamics of waiting times and waiting lists over time as a function of differing demand and supply parameters. Decreasing waiting time and increasing waiting list over certain time intervals is a possible solution, consistent with some empirical evidence.

Travers, C. M., G. D. McDonnell, et al. (2008). "The acute-aged care interface: exploring the dynamics of 'bed blocking'." Australas J Ageing **27**(3): 116-20.
Hospital effectively becomes a safety net to accommodate people with high-care needs who cannot be admitted into RAC in a timely manner. Access-block cannot be understood by viewing the hospital system in isolation from other sectors that support the health and well-being of older Australians.

Utley, M., M. Jit, et al. (2008). "Restructuring routine elective services to reduce overall capacity requirements within a local health economy." Health Care Manag Sci **11**(3): 240-7.
Discusses a mathematical modelling approach that has been used to examine circumstances under which such benefits might be realised. As an illustration of the analysis, we present results obtained using data concerning urological services, for which there would seem to be benefits associated with the introduction of a TC in only a limited range of circumstances.

Stochastic Modelling for Healthcare Management: ASMDA - 2009, in Vilnius Lithuania

Sally McClean and Adele Marshall organising a special modelling stream
Conference date: June 30- July 3, 2009 (http://www.asmda.net/asmda2009/)

6th Annual ICMCC Event: 1-3 June, 2009

University of Westminster, Psychology Business School, London, UK
Patient 2.0 Empowerment - EHR for Personalizing and Improving Care
Knowledge Management; Social and ethical aspects; Digital homecare; Future (visionary)
http://2009.icmcc.org

LAST WORDS

Six issues a year to four a year: bi-monthly to quarterly

Much has happened since 2004, when we launched Nosokinetics News onto an unexpecting world. Changing the world system of measuring and modelling the process of inpatient care is not a forest fire - more like water dripping on a stone. Yet within chaos and economic turmoil opportunities lie. Like the flapping of a butterfly's wings causing a hurricane in the Pacific Ocean, we too are breaking through.

Looking back with wonder, to that day in 1989, when I walked into Gary Harrison's office in Charleston, SC and to the combination of circumstances which led to the first mathematical model and to Sally McClean from the University of Ulster joining in, I marvel at the unique insights which their and others research efforts have given us. What wonders they worked for us, indeed we were glad.

Its a long time too, forty years, to the day when we recognised that the computer generated length of stay of discharged patients, in our department of geriatric medicine, rather than informing us of our work, misrepresented the process of inpatient care. And to the decision to create the 16 year data set, which underpins, in Sally's hands, twenty years of research effort.

Now too we know, thanks to Mark Mackay in Australia and Brendon Rae in New Zealand, that the concepts we have and are developing apply equally to general medicine as to geriatric medicine. How then do we break the good news?

Put another way, how do we solve King Solomon's Riddle—"Out of the lion's mouth came forward sweetness."

Nosokinetics News is the newsletter of the UK Nosokinetics Group

Nosokinetics is the science / subject of measuring and modelling the dynamic aspects of patient and client movement (flow) through health and social care systems. From the Greek, literally, *noso* (sickness) and *kinetics* (movement).

The group collaborates to organise conferences and disseminates news of our and others research and practical use of modelling to enhance decision making in health and social care systems.
Past issues in PDF at http://ww.nosokinetics.org/

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http://www.iol.ie/~rjtechne/millard/index0.htm

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