

More bang for your buck: using modelling & simulation to add value to healthcare evaluation studies

Sally Brailsford

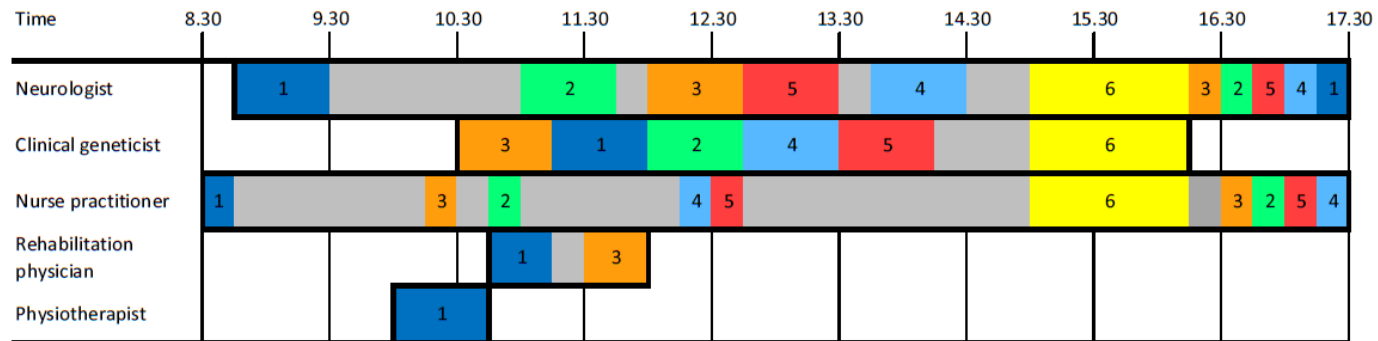
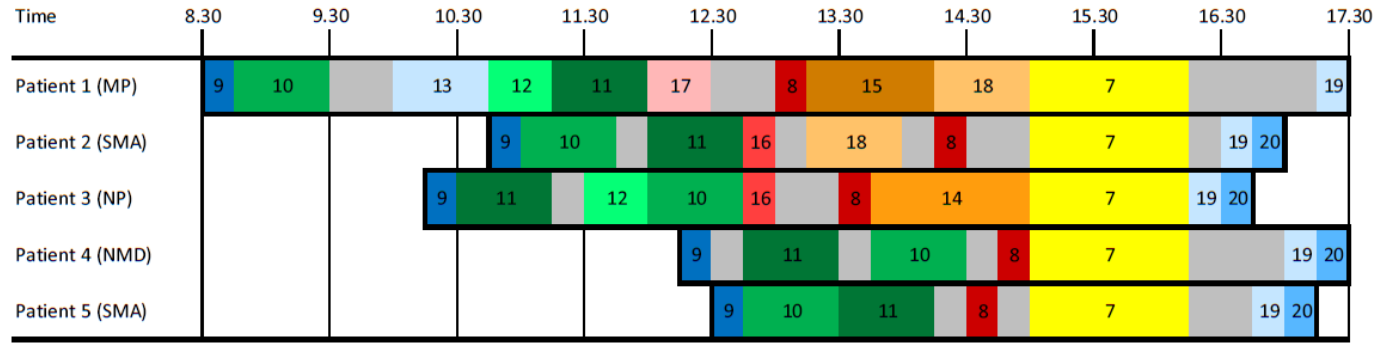
CORMSIS: Southampton Centre for Operational Research, Management
Science and Information Systems

1-minute intro to Operational Research

- “All models are wrong, but some are useful”
- A toolkit of modelling techniques and methods
- Some methods are mathematical and involve computer software ... others don't (e.g. cognitive mapping)
- Some methods assume all the parameters are known and fixed (deterministic models) ... others take account of individual variability and uncertainty (stochastic models)
- Some methods try to find the **best** solution (optimization) ... others just try to find a **good** solution (simulation)



An optimization model



Legend for physicians:

- 1 Patient 1
- 2 Patient 2
- 3 Patient 3
- 4 Patient 4
- 5 Patient 5
- 6 All
- Break

Legend for patients:

- 7 MTM
- 8 Clinical photograph
- 9 Intake
- 10 Neurologist
- 11 Clinical geneticist
- 12 Rehabilitation physician
- 13 Physiotherapist

- 14 EMG
- 15 Cardiac ultrasound / ECG
- 16 Blood examination
- 17 X-ray
- 18 Muscle ultrasound
- 19 Final meeting neurologist
- 20 Final meeting nurse practitioner

But ... behind the scenes...

$$\min \sum_{i=1}^n U_i$$

Subject To

$$\sum_{t=1}^{T-p_i+1} v_{it} = 1 \quad \forall i \quad (5)$$

$$\sum_{i=1}^n \sum_{s=t-p_i+1}^t v_{is} \leq 1 \quad \forall t \quad (6)$$

$$\sum_{t=1}^{r_i} v_{it} = 0 \quad \forall i \quad (7)$$

$$\sum_{t=1}^{T-p_i+1} v_{it} + p_i - d_i - 1 - MU_i \leq 0 \quad \forall i \quad (8)$$

$$v_{it} \in \{0, 1\} \quad \forall i, \forall t < T - p_i$$

$$U_i \in \{0, 1\} \quad \forall i$$

$$c_2^* = \min \sum_{i=1}^n U_i$$

Subject To

$$t_{k+1} - t_k - \sum_{i=1}^n p_i u_k^i \geq 0 \quad \forall k \quad (14)$$

$$t_k - \sum_{i=1}^n r_i u_k^i \geq 0 \quad \forall k \quad (15)$$

$$t_k + \sum_{i=1}^n (p_i - d_i) u_k^i \leq 0 \quad \forall k \quad (16)$$

$$\sum_{i=1}^n u_k^i \leq 1 \quad \forall k \quad (17)$$

$$\sum_{k=1}^n u_k^i + U_i = 1 \quad \forall i \quad (18)$$

$$u_k^i \in \{0, 1\} \quad \forall k, i$$

$$U_i \in \{0, 1\} \quad \forall i$$

A discrete-event simulation (DES) model

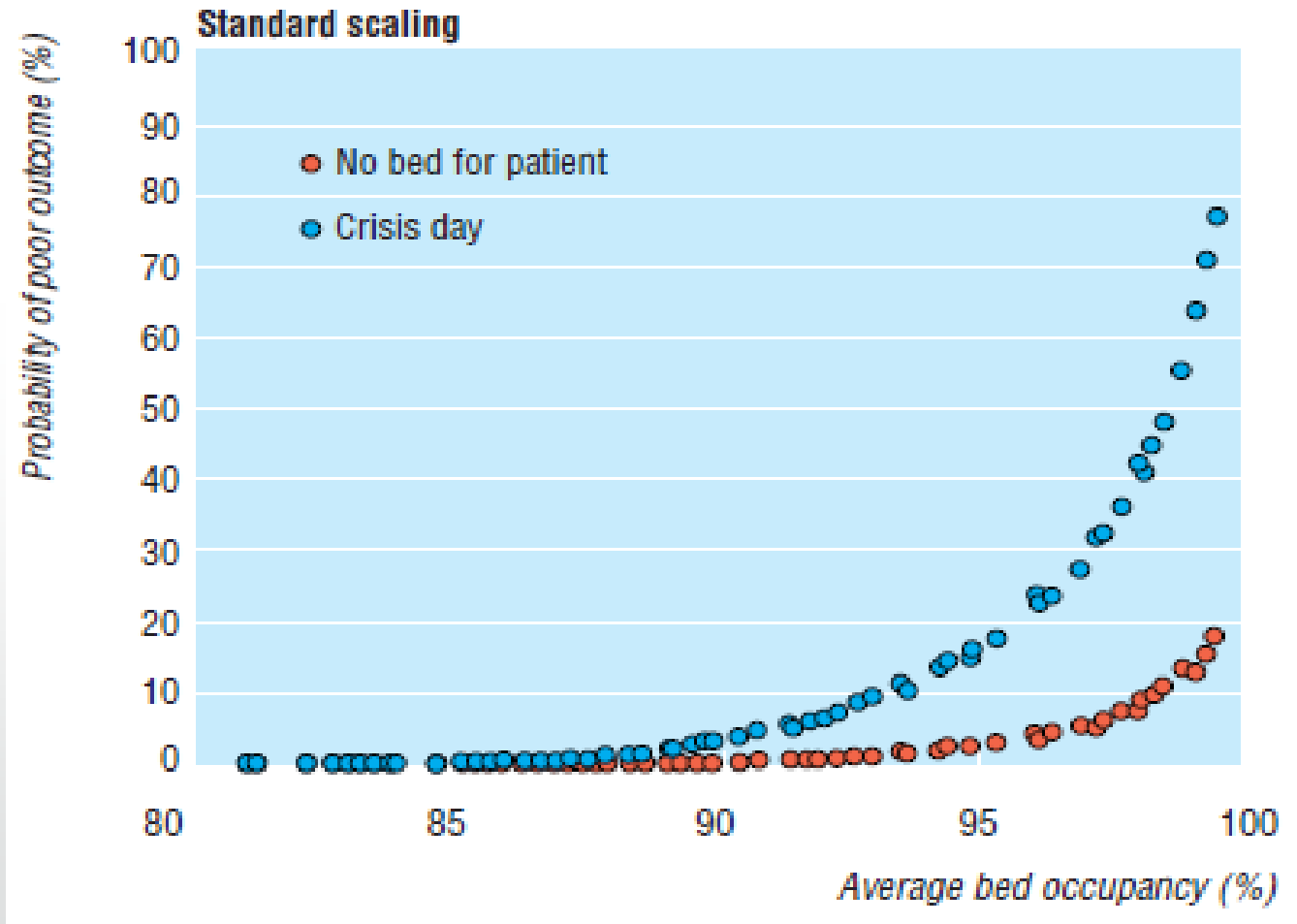


Example 1: Bagust et al (BMJ, 1999)

- A (fairly) simple discrete-event simulation model which showed the impact of variability in arrivals and LoS
- Performance measures:
 - the annual % of emergency arrivals who cannot be accommodated owing to a lack of available beds
 - the % of days in a year when there is at least one such patient (termed a crisis day)
- Influential on government policy about bed occupancy targets

Bagust, Place & Posnett (1999) Dynamics of bed use in accommodating emergency admissions: stochastic simulation model. *BMJ* 1999; 319:155-159

Results



Example 2: Diabetic retinopathy screening

- Joint research with Ruth Davies and Chris Canning in the 1990's
- Population-level discrete-event simulation model of the natural history progression of retinopathy in individual patients with diabetes
- Data on incidence, prevalence and progression from the literature (mainly the UK Prospective Diabetes Study and the Wisconsin Epidemiologic Study of Diabetic Retinopathy) and on screening modalities from clinical trials
- Model run for 30 years (1990-2020) in many different UK populations: wide variety of screening methods and policies were tested
- Outcome measure: cost per sight year saved



Results

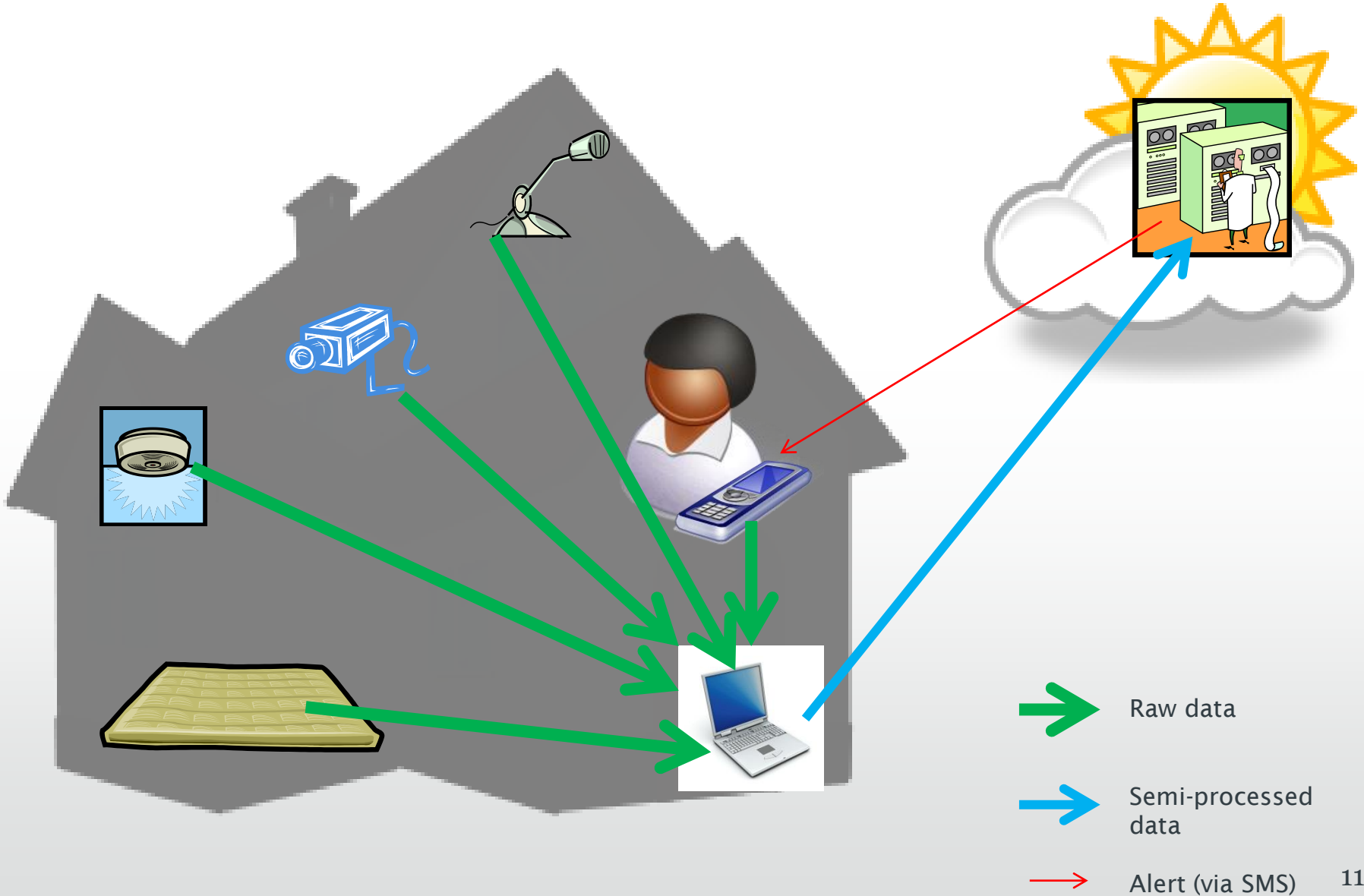
- Mobile van was the most cost-effective method (at the time)
- Differences between methods were small in comparison with compliance issues: getting people to attend is key
- Led to further research into ways of including human behaviour in simulation models: e.g. modelling mammography attendance

R.M. Davies, P.J. Roderick, C. Canning and S.C. Brailsford (2002). The evaluation of screening policies for diabetic retinopathy using simulation, *Diabetic Medicine*, **19**: 762-770.

Brailsford S C, Harper P R and Sykes J (2012). Incorporating human behaviour in simulation models of Screening for Breast Cancer. *European Journal of Operational Research*, **219**: 491-507.

Example 3: the PAM project

- Joint EPSRC-funded research with engineers Christopher James, John Crowe and Evan Magill (2007 – 10)
- Enabling health, independence and wellbeing for psychiatric patients through Personalised Ambient Monitoring (PAM): evaluating the potential use of a system of wearable and ambient sensors to monitor activity patterns in people with bipolar disorder



OR modelling in PAM

- A natural history model for bipolar disorder was developed and used to test the sensitivity and specificity of the PAM algorithms
- An Excel-based microsimulation model was used to conduct a “virtual clinical trial” on thousands of synthetic patients, using a combination of data from the clinical literature and artificial data
 - Could PAM possibly work? What would a PAM system look like?
 - How accurate (and/or reliable) would it have to be, to be useful?
 - Can we describe the types of patient who might benefit?
 - Where should the engineers focus their attention? Where are the critical weaknesses in the system?

Results

- The effectiveness of PAM was highly dependent on the individual's personal choice of sensors and prodromes (symptoms & behaviours)
- PAM was found to be inadequate for almost all the personalised choices of two prodromes only, but efficient for most choices of three prodromes
- The model informed future design decisions, even though the PAM system itself did not even exist when the model was being developed!

Brailsford, S.C., Mohiuddin, S. and James, C.J. et al. (2013). A multi-state model to improve the design of an automated system to monitor the activity patterns of patients with bipolar disorder. *Journal of the Operational Research Society* 64, 372-383

Summing up .. and reflecting on data

- The Bagust et al model used very little real data, but it had a major impact on national target-setting policy
- The retinopathy model used data from a wide variety of sources, not all from the same setting (or even country)
- The PAM model was exceedingly hypothetical, even though it did use a limited amount of data from the clinical literature
- These models may all have been “wrong” .. but they were undoubtedly useful

The benefits of OR modelling

- Provides a risk-free playground for experimentation and is vastly quicker and cheaper than trying things for real
- Provides a neutral framework for discussion: engages stakeholders and forces clarity through making assumptions explicit
- Can inform future work, data collection or the design of systems/things which do not yet exist
- Powerful when used in conjunction with other research methods for triangulation, experimentation etc
- You can always learn something from a model, even if you have no data
- A smart way to squeeze the last drop of value from your data!