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What is a 'generic' hospital model?

Adrian Fletcher and Dave Worthington

The Department of Management Science
Lancaster University Management School
Lancaster LA1 4YX
UK

WHAT IS A 'GENERIC' HOSPITAL MODEL?

Adrian Fletcher, Economics, Statistics and Operational Research, Department of Health, Quarry House, Quarry Hill, Leeds, LS2 7UE

Dave Worthington, Department of Management Science, Lancaster University, Lancaster, LA1 4YX, UK

Abstract

This working paper addresses the question posed in the title via a survey of 20 or so experienced healthcare modellers and a literature review of over 100 books and articles. Four levels of 'genericity' are proposed: generic principle model, generic framework, setting-specific generic model and setting-specific model. The third and fourth of these are then chosen as the focus for a further in-depth examination to extract lessons relevant to the problem of building a 'whole-hospital' model for emergency patients. Many examples of models of individual hospital departments are found and a much smaller number of multi-department models. Many of these do not report validation or implementation processes. Nevertheless potentially valuable lessons can be learned.

1. Introduction

The primary motivation for this working paper was the experience of one of the authors (AF) who had developed along with Department of Health colleagues an Accident and Emergency (A&E) simulation model which was in some sense 'generic'. This 'generic' model had proved to be a valuable tool in the UK's drive to improve the performance of hospital A&E departments, see Fletcher et al (0) for details, and he was interested to see whether a similar approach could be extended to a whole-hospital simulation for 'emergency' patients, i.e. all patients other than waiting list patients.

However it soon became clear that the term 'generic' in the context of (hospital) modelling meant different things to different people, with good reason.

Healthcare systems such as the NHS typically run many hospitals all with similar objectives, in the face of broadly similar demands and using broadly similar resources. Hence, at least in principle, 'generic' hospital models are viewed as a 'good thing', with their 'genericness' suggesting the potential for understanding general problems faced by many hospitals and the general solutions which might exist to deal with them.

However hospital models almost invariably imply a computer model, where 'genericness' of software components implies potential for multiple uses as a reliable component in a range of different programmes. Whilst random number generators and mathematical algorithms are good examples of highly transportable software components, code to perform any specified set of actions (e.g. a hospital model) is also transportable. Whether or not it qualifies as 'generic' perhaps depends on whether or not there is an application that requires this particular code.

Enter the OR modeller who aims to represent a situation in 'sufficient detail' for decision making, but who is happy to make use of whatever is available as long as it is 'good enough' to improve understanding and aid decision making. If he/she is willing to contemplate using a mathematical formula on the grounds that it might provide an adequate fit to the situation, why not contemplate using someone else's hospital model, especially if it can be tailored (to some extent) to the new situation. Whilst such a transportable hospital model does not strictly qualify as 'generic' according to either of the two senses above, they are nevertheless qualities to which it can be seen to aspire.

This working paper reports the results of two preparatory exercises. The first was an email request to experienced healthcare modellers (mainly members of the European Working Group on Operational Research Applied to Health Services – ORAHS) asking them about their experiences and thoughts on 'generic' models. The second was an extensive literature review based on an initial list of over 350 potentially useful papers.

The objectives of these preparatory exercises were to assess published knowledge and experience of the following:

1. The characteristics of 'generic' models compared to 'specific' models
2. Modelling flows of emergency patients through departments in acute hospitals (assumed to be A&E, bed management, surgery, critical care and diagnostics)
3. Modelling flows **between** the above components
4. Lessons about design, validation and implementation of discrete event simulation models in hospitals
5. Comparison of success of specific models versus generic models in hospitals, particularly for emergency patients

The remainder of this working paper is organised as follows. Section 2 describes the email survey of healthcare modellers, and section 3 describes the literature review process adopted. Section 4 then presents the results of these two processes, starting with a clarification of the term 'generic' before moving on to discuss modelling experiences and lessons relevant to the main stages of emergency patients' routes through a hospital: A&E, bed management, surgery, critical/intensive care and diagnostics. The challenge of modelling multiple hospital departments is then discussed before a final subsection on general lessons for the design, validation and implementation of simulation models in this context. Finally section 5 provides a summary of the main findings resulting from these exercises.

2. Email Survey of Experienced Healthcare Modellers

Our interest in the topic of 'generic' hospital models coincided with the 2005 annual meeting of the European Working Group on Operational Research Applied to Health Services – ORAHS – at Southampton University. Discussions with participants indicated a high level of interest in the topic, plus a variety of experiences and views!

We therefore followed up these discussions with an email request to 20 or so members of the group who were experienced in healthcare modelling asking them:

1 What does a generic model mean to you?
2 Have you come across any good/bad attempts to devise generic models?
3 What lessons do you think are worth taking away from these examples about the value and challenges associated with developing generic models?

This brief survey was extended a little later to a small number of OR practitioners in the Department of Health.

The quantity and quality of the responses was excellent, reflecting the central importance of the general issues to the interests and experiences of work of healthcare modellers. In responses were received from 20 modellers, ranging from the succinct half page to a 14-page Discussion Note! See Acknowledgements for a list of respondents.

These responses managed to anticipate many of the issues subsequently appearing during the literature review, plus some extra valuable insights and examples.

3 The Literature Review Process

Stage 1

The search started with some relevant papers identified by a fellow researcher, Murat Gunal in his PhD literature search on a related issue of modelling key drivers of hospital performance. Forty three of the papers provided by him were of particular relevance to the above objectives. These papers referenced more than 350 further potentially useful papers in total.

Stage 2

Clearly some sort of prioritisation method was needed in order to focus on the defined objectives. Here papers were prioritised using the method shown in Table 1 , (based only on the paper title).

Table 1: Prioritising literature search papers

Priority	Apparent subject matter	Number of papers
1	Modelling A&E departments	37
2	Modelling other components of emergency care provision (bed management, critical care, surgery, diagnostics)	99
3	Hospital wide modelling. General discrete event simulation or system dynamic model design, validation and implementation techniques	120
4	Modelling other hospital provision (e.g. outpatients)	82
5	Simulation modelling in other industries	34

The review then concentrated on papers of priority 1-3. The volumes and content of papers/books in these categories appeared to be sufficient to cover my objectives. Specifically, these papers would provide knowledge of models developed to examine emergency care provision in hospital, plus lessons about building and implementing discrete event simulation models in hospitals and elsewhere. It would also be possible to assess whether any model was 'whole system' in linking different components of emergency care provision. Finally it would be possible to compare 'specific' and 'generic' models

Searches for the identified category 1-3 papers/books, found around 100 of the 250+ papers/books through the Lancaster University library – many of the papers were from more obscure conference proceedings and/or journals that weren't immediately available. These papers gave a good coverage of the stated objectives.

Stage 3

In order to check that no recent relevant papers had been missed, journals which had been referenced in the 100 papers identified above were assessed. This generated a list of 20 key journals.

These journals were then searched for papers published after 1998 with titles containing any of the following key words: occupancy, emergency, hospital, operating, theatre, surgery, surgical, simulation, staffing, schedule, scheduling, intensive care, ICU, bed, admission, patient, modelling, capacity, critical care, health, resource, biochemistry, radiology, CT, clinical, laboratory. 1998 was chosen, because a key review of the literature in simulation modelling in health care was conducted by Jun et al in 1999. This search identified 15 more priority 1-3 papers. Hence copies of 105 papers and 10 books were obtained.

4 Results from the literature search and email survey

This section summarises the results and ideas emerging from the literature review and the email survey. The four main subsections follow the first four objectives of this paper, with the fifth objective being addressed within the subsections as appropriate:

1. The characteristics of 'generic' models compared to 'specific' models.
2. Modelling flows of emergency patients through departments in acute hospitals (assumed to be A&E, bed management, surgery, critical care and diagnostics).
3. Modelling flows **between** the above components.
4. Lessons about design, validation and implementation of discrete event simulation models in hospitals.
5. Comparison of success of specific models versus generic models in hospitals, particularly for emergency patients.

4.1 The characteristics of 'generic' and 'specific' models

George Box: "All models are wrong, some are useful."

4.1.1 Different interpretations of generic models:

Lowery (1) asserts that a model should be based on the following principles: general, flexible, intuitive and simple, and include default values for system parameters.

Sinreich et al (2) discuss three levels of genericity – the most generic being high levels of abstraction that can model any system and scenario, the least generic being those that can model only one specific system. In the middle are models that can model any provider of a similar process. The responses to the informal survey broadly agree with this framework. This generates four broad types of model in descending order of abstraction, and transportability:

Level 1. A broad 'generic principle' model – e.g. a general theoretical queueing system or general economic models of supply vs demand vs cost. These models are not setting specific, and the messages can be transferable across industries/settings.

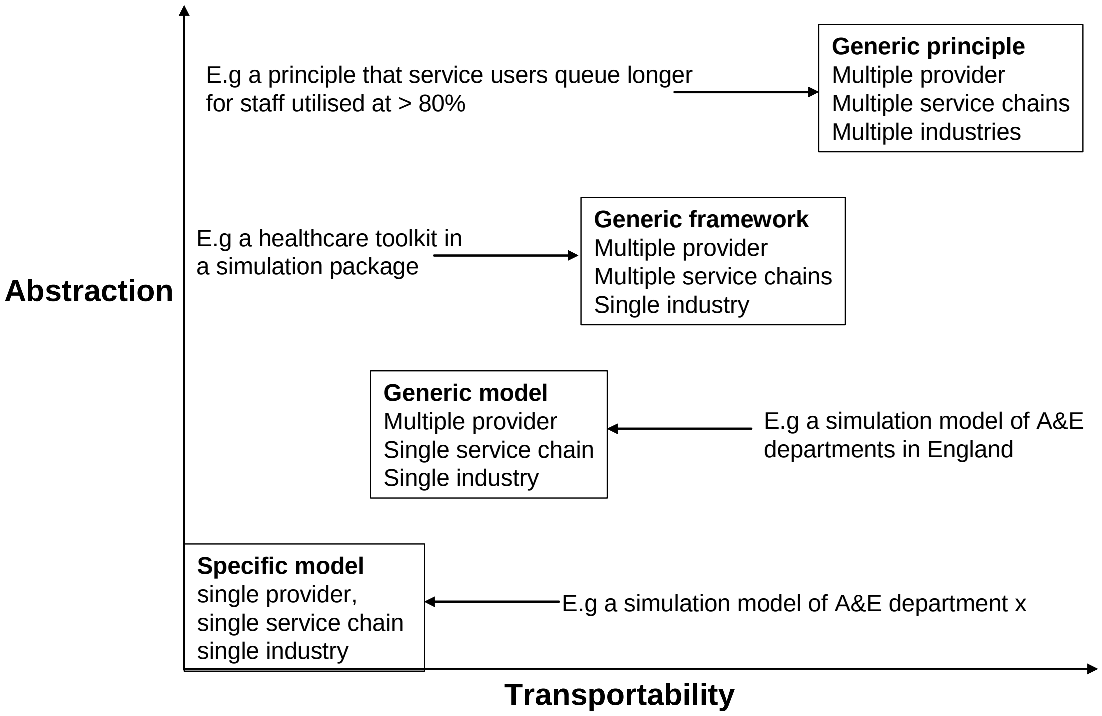
Level 2. A generic framework that could be developed into a toolkit. For example, healthcare is characterised by issues of waiting, availability of staff and equipment, beds, theatre time etc. These issues could be grouped into a theoretical framework and/or toolkit for modelling healthcare systems with predefined modules that represented these generic processes. These could be linked to generate a system of the user's choosing. Along with local input data, this toolkit could enable the user to generate a locally specific model. For example, the toolkit might allow a generic operating theatre to be created, linking it back to A&E and forward to intensive care. This sort of framework could also be used to illustrate general principles as in a 'level 1' model. For example, it could show that operating theatres of certain sizes and throughputs need a certain number of inpatient beds to support them. To make a model locally specific, the user would need significant local knowledge – for example that they have 4 operating theatres of size x, y beds with z days length of stay etc.

Level 3. A setting-specific generic model. In this model, the structure stays unchanged, but could be used by any providers of the same type of service. For example A&E departments would need a generic A&E model, outpatient departments a generic outpatient model. The model structure doesn't change between providers, but the input data does.

Level 4. A setting-specific model. This provides a model of a particular local service and is not (necessarily) transportable to another provider of the same service.

These levels of genericity are summarised in Figure 1

Figure 1: The spectrum of genericity



4.1.2 Software issues

These issues can also be considered in terms of software/programming dimension in descending order of genericity.

- Programming language – most generic!
- Simulation package
- Modelling frameworks (e.g. health) within a package
- Generic model built within a package/framework for broad applicability
- Specific model built within a package/framework – most specific

4.1.3 Model reuse

Robinson et al (18) discuss a spectrum of reuse, from "code scavenging" up to full model reuse and weigh these considerations against development cost. A cycle of "grabbing and glueing" old ideas/models/pieces of code, running them, using if workable, otherwise rejecting and retrying is proposed. The key benefits of model reuse are identified as time and cost and consistency of output, obstacles being time/cost on projects to support reusability, plus systems architecture issues. Pitfalls are around required levels of abstraction, and "force fitting" inappropriate models.

4.1.4 Generic vs specific comparisons

The focus of the research of which this working paper is part corresponds to level 4 (specific) and level 3 (generic) models. Proposed simple definitions are as follows.

> A <u>generic model</u> is capable of modelling alternative providers in the same setting(s) with the same basic model structure and just a change of input data.
>
> A <u>specific model</u> is of a particular local service and is not designed to be transportable to another provider of the same service (although it may be).

As implied in these definitions and Figure 1, the only difference between these models is the design objective of transportability. Figure 1 uses the example of an A&E model. Using the above definition of generic and specific models, both models would be of an A&E department in the English NHS. However the generic model would be designed to be usable in any A&E department, whereas a specific model may only be applicable in one.

Beneath these fairly simple definitions lie a host of different dimensions, issues and success factors. Some key factors identified by survey respondents and the literature are shown in Table 2.

Table 2: Key factors in generic and specific models

	Generic Model	**Specific model**
Hardware/software requirements	Inexpensive or free	Possibly inexpensive or free, but some local investment in software may be agreed
Post development user support	Geared towards handover to multiple (geographically spread) users	Geared towards handover to user(s) at the particular department
Level of detail	As simple as possible, but inclusive of significant processes in multiple departments	As simple as possible. Inclusive of significant processes in the particular department
Validation/quality assurance	It needs to represent the performance of numerous departments and/or may be tailored to represent the performance of particular departments.	It needs to represent the performance of one department
Data quality required	Depends on type of input and level of accuracy required	Depends on type of input and level of accuracy required
Availability of test 'starting' data	Important – perhaps 'national average' and/or local history	Important – local history
Representation of local issues	As high as practically possible in a generic framework. Through the generic design and data input.	High – through model design as well as input
Use of model	To build broad understanding of an issue and/or to be tailored to answer specific local questions.	To answer specific questions in detail
Conflict with existing models	High potential for conflict – not likely to replace existing models where they exist	Likely to replace existing models
Local desire to use it	Depends on perception of quality, coverage, other current models	High? they asked for it to be built
Local capability to use it	Depends how hard it is to use, and ability of user	Depends how hard it is to use, and ability of user
User knowledge of inner workings of model	Initially low, depends how well it is described in user guide etc	User(s) likely to have been involved in model build, so initially higher
Scope	Depends on problem	Depends on problem
Required technical capability of user	Low	Low
Design process	Working with national/group experts, validation at one/more departments	Working with local expert(s)
Level of accuracy locally	Possibly lower	Possibly higher
Level of insight	Depends on model. Anything from broad discussion of issues(?) to accurate and detailed identification of local improvement strategies	Depends on model. Anything from broad discussion of issues(?) to accurate and detailed identification of local improvement strategies
Level of use	In multiple providers and/or at policy level.	In a single provider
User input/output	Must be succinct, clearly defined and	Possibly looser, depending on local

	structured	circumstance
Design objective	Specific to those elements which are common but flexible enough to model the differences. Similarities to local provision outweigh the differences.	Specific to the system and provider being modelled. Transportability not considered
Appropriateness of use	Clearly defined systems for which the model is applicable, clear identification of when modification of input data is appropriate and when new structure is required	Clearly defined systems for which applicable – greater likelihood of local adjustment of model structure as required

4.1.5 Generic models - Summary

Clearly the discussion of what constitutes a generic model is complex and multidimensional. Based on evidence from literature and responses to an informal survey, a framework leading from specific models up to generic principles has been defined based on key dimensions of transportability and abstraction. Other factors in defining genericity include software issues and levels of code/model reuse.

Considering key issues and success factors further illustrates the multidimensional issues when comparing generic and specific models. There are obvious differences, but also perhaps a surprising amount of similarity between generic and specific models on many of these dimensions.

4.2 Modelling flows of emergency patients through individual components of acute hospitals

4.2.1 A&E – general lessons and previous literature reviews

Jun et al (4) identify numerous applications of discrete event simulation in A&E departments. The key output in all these papers was patient time in A&E. Garcia et al (5) and Blake and Carter(6) analysed the impact of using “fast track” to reduce waiting times in A&E, finding that significant improvements could be made with minimal extra resource. Kraitsik (7) and Kirtland (8) made similar findings, also that different practices in diagnostic labs and patient placements in A&E departments would give significant improvement. McGuire (9) recommended alternatives to improve A&E performance including extra admin staff, fast track patients and different workforce practice. Ritondo et al (10) found that different practice on ordering tests had high potential.

Jun also identified numerous studies of workforce scheduling in A&E departments. Draeger (11) found that alternative nursing staffing schedules could reduce patient waits at no extra costs. Evans (12) and Kumar (13) found similar results. Badri and Hollingsworth (14) examined different scheduling rules, staffing patterns and patient allocation rules, implementing changes as a result. Bodtker et al (15) and Godolphin et al (16) made similar findings using simulation. Liyanage and Gale (17) used queueing model techniques to investigate similar scenarios with similar results.

Horton (18) discusses the use of “rapid process improvement” to improve an ED in America. This technique tests changes on a small scale and expands when they are successful. Numerous changes such as a fast track area with dedicated nursing staff, integration of diagnostic processes, data micromanagement, changes to discharge processes and the critical care unit improved patient flow in different ED’s .

Carter (19) discusses scheduling of ER doctors. The problem was formulated and numerous scheduling rules investigated in two hospitals. Nothing on implementation.

4.2.1.1 A&E Generic models

Sinreich et al (2) discuss a generic A&E simulation model. They draw on Lowery (1) to assert that a model should be general, flexible, intuitive and simple, and include default values for system parameters. The paper also discusses three levels of genericity. The most generic are models with high abstraction that can model any system and scenario – classed as difficult to use. In the middle are models which can model any system with a similar process, classed as simple and intuitive after a brief introduction. The least generic (and most specific) is at low levels of abstraction, which can only model one specific system, classed as easy to use. Their model is aimed to be at the middle level. By observing five different A&Es, five key patient types were identified. Generic process charts were developed. Mathematical modelling suggested that a general simulation tool based on a unified process could be developed. Patients arrivals are modelled by Time of Day (TOD), grouped by testing requirements. Validation and implementation are not discussed.

Miller et al (20) discuss a generic simulation modelling approach to EDs using a reusable generic simulation framework – EDSim. They draw on case studies in America to discuss typical modelling interventions. EDSim can answer questions around issues such as discharging policy, overall capacity, lab processes, demand rises etc. Issues of validation are not discussed. A typical consultancy process is described, including process modelling workshops, interviews and data collection to identify key bottlenecks. Numerous successful projects are claimed using this tool.

Centeno et al (21) describe a model that combines Linear Programming with simulation to reduce staffing costs in an ED. They define generic flows of patients and service time distributions for nurses and doctors at each process. Inter-arrival times of patients are estimated by time of day, and optimal resources/shift patterns are generated through Integer Linear Programming for different levels of demand. Model validation methods are not clear. Initial data suggests a particular ER, but results are presented as a generic model. No evidence of implementation.

4.2.1.2 A&E - Specific models

Takakuwa et al (22) discuss a simulation model of an ED in Japan with long waiting times. Coverage includes “A&E” processes, plus surgery. It is unclear how bed availability for surgery and medicine is modelled. Diagnostics are based on the room rather than staff. Patients are grouped by arrival type (ambulance, walk ins) with specific routes. Resources modelled include clerks, treatment cubicles, medical staff and nurses and diagnostic rooms. It is unclear how TOD, DOW are modelled. The outcome is “congestion factor” and total patient time under baseline and other scenarios (e.g staffing, beds etc). Nothing on validation and implementation.

Blasak et al (23) discuss a simulation model of an ED and “Medical Telemetry” unit (like a medical admissions unit) in Boston, US. The objective was to reduce ED patient time, including time waiting for bed. Patients are categorised by arrival time, arrival mechanism (walkins, ambulance, direct) and urgency. Procedures modelled were diagnostics, staff availability (doctors, nurses, healthcare assistants), patient transport, cleaning, room availability, bed delays, other hospital transfers (in telemetry unit). Outputs were patient time by process and total, queue length by process and utilization of staff, rooms and beds. Validation was not discussed. Results “directed the change process”. The Operations Director was involved and is the author.

Rossetti et al (24) discuss a simulation model of an ED in Virginia, US. The objective was to increase patient throughput and optimise staff utilization by altering staff schedules. Design covered patient groupings, doctors and nurses, beds and diagnostics. TOD/DOW patterns were modelled. Validation was well described and included computer system and on site data collection, local discussions of model design and results, and comparison with historical waiting time data. There were three stages of on site data collection: patient arrival and wait characteristics, staff service times and transport and routing times. Different staffing schedules were compared for effects on patient throughput and staff utilization. Nothing on implementation.

Baesler et al (25) discuss a simulation model in an ER in Chile. Demand increases were expected and the model was built to show potential impact on patient waiting time. The model covers patient flow for non admitted patients. Doctors, rooms, paramedics, reception staff and testing were included. No obvious accounting for TOD, DOW. Nothing on validation. Scenarios on demand rises and capacity changes resulted in recommended staff levels. Nothing on implementation.

Miller et al (26) discuss a simulation model of an ED in the US to examine process improvements and expansions. A six sigma methodology generated potential improvements. A conceptual model was developed in Visio with clients. Nothing on what resources were included, or validation. Key improvements were changed discharge process, more beds, improved testing. The key consultancy issue was defining scope with clients – 20 model design iterations were required. Nothing on implementation, but the model is “handed over”.

Wiinamaki et al (27) describe a simulation model at an ED in America which because of demand increases, required a new build. It is unclear which resources are directly modelled (e.g. doctors, testing etc), but all A&E processes, clinical decision and admissions units are modelled. Nothing about validation. Some recommendations were accepted – extra X Ray space, new triage and less acute beds.

Blake and Carter (28) discuss a simulation study in a children’s ED in Canada. The objective was reduced waiting times for patients with primary care conditions. All key processes and personnel were included. Data population was through the hospitals systems plus direct observation (particularly doctors workloads for multitasking issues). Key outputs were total time and time to first assessment. TOD/DOW factors were modelled. Validation was against actual historical data. ANOVA modelling suggested junior and senior doctor availability were the key factors. A Fast track minor stream was also modelled. The model contributed to the implementation of numerous new practices such as a fast track and development of a new clinic.

Badri and Hollingsworth (29) discuss a simulation model of an ER in the UAE to investigate the effects of policy changes. ER activities were included for five types of patients (but nothing on diagnostics or waits for bed). Service times at each process were generated. Medical, pharmacist and admin staffing levels were modelled, plus the number of ER beds. No obvious recognition of TOD/DOW demand issues, but staff shift patterns incorporated. Validation was through interviews with local experts and comparison of total time data. Alternative scenarios of changed patient priorities, diversion of minor patients and staffing profiles were modelled, which generated implemented (and monitored) recommendations.

Lane et al (30) discuss a system dynamics (SD) model of an A&E department, through to bed management in England. The objective was to reduce patient time in A&E (particularly for admitted patients). SD was chosen above DES to provoke a more strategic perspective of the system. The model included all A&E patient processes (including testing) including bed management (including rules on elective surgery cancellation). Doctor utilization was included. TOD but not DOW issues were included. Validation was through discussion with local experts and comparison with observed data. Numerous scenarios were run including bed capacity and changes in demand patterns. Nothing on implementation.

Komashie and Mousavi (31) describe an A&E simulation model in an English hospital. Objectives were to understand the drivers of patient time in A&E, and causes of variability. Model scope included the Medical Admissions Unit and diagnostics. A&E doctors and nurses are modelled. TOD issues were included. Observation of some process times was conducted, plus computerised data. Validation was through demonstration to key local experts and comparison with KPI's. Scenarios included adding cubicles, adding nurses/doctors, improved admission process. Significant potential improvements were observed. Not clear whether results were implemented.

Samanha et al (32) discuss a specific simulation model of an American ED. Objectives were to show the ED process and bottlenecks and assess improvement options to reduce patient time in ED. Coverage is all patients through the ED, including impact of testing and hospital bed availability. Data on arrival and process times was collected through observation. ED resources specifically modelled were rooms, doctors and other staff. Validation was primarily 'open box'. Scenarios included changed pathways, ED resizing, fast-tracking patients. The model found that process changes would avoid the need for expansion. The results were implemented.

Mahapatra et al (33) discuss a simulation model of an American ED. The objective was to reduce patient time using a fast track centre. Data was collected on patient arrival times by case mix, waits by process and staff schedules. This was combined with interviews and observation of service times. Patient flow through triage, assessment, testing, treatment and discharge/admission is modelled. The ED is split into three sections – Critical care for the most acutes, and Intermediate care/Alterna care for less acutes. These, plus triage, diagnostics and follow-up treatment are all modelled in submodels. TOD and DOW are accounted for. Validation was by open box and black box methods. Scenarios showed that expansion of the fast track Alterna area would improve throughput significantly. Nothing on implementation.

Gonzalez (34) discusses a simulation model of an ED in Spain. Patient routings are not typical of English A&E departments. Patient time and queue length are key outputs, doctors, nurses key are resources, testing, assessment, treatment, waits for bed are key processes. Open box and closed box validation were used. Scenarios around staffing, patient routing and other staff were run. Nothing on implementation.

4.2.1.3 Summary – A&E models

There is more evidence of specific A&E models than generic. Many examples are in American ERs, which have different designs to English A&E. Key outputs are typically time in A&E, queue length and staff/room utilization. Models often include A&E medical, nursing and clerical staffing, examination cubicles, diagnostics, decision to admit and bed management. Specific patient types are often modelled, often by TOD and DOW. Models occasionally directly model capacity constrained beds, diagnostics and surgery, but more often as time distributions. Techniques are mainly discrete event simulation, but some evidence of scheduling, queueing models and system dynamics. Design is usually through discussion with local experts. Data collection is generally through computerised records, also occasionally work studies and local consultation. Validation is discussed less, but is usually through comparison with computerised records, and/or "open box" type validation with local experts. Scenarios include workforce scheduling, changed roles, bed management, fast track patients, diagnostic changes and overall capacity changes. Implementation is not widely discussed, but some evidence that both generic and specific models have similar designs and have been used with broadly equal success.

4.2.2 Bed management

Jun et al (3) found numerous examples of bed management simulation models. Butler et al (35) found that reallocation of beds through integer programming and reducing LOS could reduce patient misallocation. Other similar models were written by Hancock et al (36) and Wright (37). Gabaeff (38) used work study and simulation to examine requirements for emergency beds (and medical testing) and highlight mismatches between demand and supply. Vassilacopoulos (39) developed a simulation model of bed requirements that showed with waiting lists and smoothed demand, high occupancy rates could be achieved. Emergency department bed planning models were also developed by Altinel and Ulas (40), Freedman (41), Lennon (42) and Williams (43).

Adan (44) discusses an admission planning tool. Sub specialty patient mix determines resource requirements (e.g. beds, theatres, nursing, intensive care). A linear programming model was developed to maximise patient flow and resource utilization.

4.2.2.1 Bed Management: Generic models

Bagust et al (45) discuss a generic, spreadsheet based simulation model of emergency inpatient bed requirements at a hypothetical acute hospital. Notional emergency bed capacity is defined, and randomised admission rates per day and LOS around seasonal and DOW patterns are generated. Data from two hospitals are used for validation, but the model is generic. Model granularity is daily - TOD not included. Key outputs are risk of non admission of emergency patients, and frequency of occurrence. Validation techniques were unclear. Scenarios included growths in emergency demand, different occupancy levels, LOS changes, resource pooling. Nothing implemented - model is a discussion tool. Key message is around the risks of high underlying utilisation.

Nguyen et al (46) present a generic model to generate an optimal number of beds in a unit, based on trading the potential number of transfers due to lack of space, the number of days with no possibility for S unscheduled admissions and the number of days with at least U unoccupied beds.,i.e the department is a container that must not overflow, nor remain too empty. The algorithm minimises the mean and standard deviation of each of these. The model was validated on a surgery department and two internal medicine departments, and gave better performance against these output measures than current bed allocation methods. The methodology is generic.

Gorunescu et al (47) discuss a bed management model using queueing theory. The model is validated on a trust but is generalisable. By assigning costs of refused access, occupied and unoccupied beds, the model can generate the optimal number of beds.

Mackay (48) discusses a flexible generic model that can be used at regional, hospital or specialty level in South Australia. Required data is patient type, occupancy and length of stay. It is a double compartment model - patients are split into two types (e.g short/long LOS). Daily/monthly occupancy rates are calculated. The model fitted well to actual occupancy data, the author suggests the model is generalisable.

Harrison (49) discusses the use of mixed exponential occupancy distributions and patient flow models for health care planning. He finds that in Britain, combining two exponential distributions better represents long term care patients. This is not the case in American hospitals, implying different management practices.

4.2.2.2 Bed management: Specific models

Harper and Shahani (50) discuss a bed management simulation model for an English hospital. Inputs include hourly, daily and monthly arrival and discharge rates, LOS and beds by patient category - generated using CART. Patients are assigned to alternative units when beds aren't available in the primary unit. "Refusal rates" are modelled (a bed is unavailable in the preferred unit). Validation was against a year's occupancy/refusal rates. A case study examines the adult medicine specialty, showing that average based techniques that ignore variability produce misleading results. Recommendations have been implemented – bed requirements, combining bed pools, patient categorisation, admission policy.

Harris (51) describes a simulation model of surgery ward beds (pre/post op). Surgery schedules by type of patient/consultant, and LOS and variability for each patient type are required. The model calculates average, and variability of bed requirements. Scenarios included improved theatre schedules and bed management policies. Nothing on implementation, although it was to be used in a South Wales hospital.

Dumas (52) describes a model in an American hospital to improve bed allocation and patient placing policies between specialty. Demand, the admission process, and inpatient patient movements through to discharge were modelled. Specialty level demand is generated and each day attempts to be placed in that bed pool. If no beds are available by the end of the day, they are "misplaced" in another specialty. LOS's are sampled from the specialty level distribution. Admission and discharge profiles are by DOW. KPI's are occupancy and misplacements. Validation was through structured sessions with bed managers to assess behaviours and criteria. Numerous patient placement rules were tested, and better bed allocations by specialty generated to reduce misplacements and standardise occupancy. Nothing on implementation.

Vissers (53) discusses a bed allocation procedure by specialty in a hospital with access problems. The model takes projections in demand and changes in LOS to generate optimal bed allocations based on actual use. Nothing on implementation.

4.2.2.3 Summary: Bed management models

There is an even spread of published literature between generic and specific bed management models. Some models cover a single specialty, others the whole hospital, others go to health authority level. Surgery capacity was sometimes modelled. KPI's were typically risks of beds being unavailable, misplacements, "trolley waits" and surgery cancellations. Simulation is commonly used, but often spreadsheet based, occasionally combined with integer programming to determine optimal bed mixes. Key modelled factors are projected bed occupancy using patient arrival patterns (by type), LOS and known variability. Mathematical modelling is occasionally used to assign costs of rejections and unoccupied beds to calculate optimal bed numbers. Most models worked at the daily level – most accounted for demand variability by day of week, but most did not include time of day issues. Enough data was usually available from computer systems for design and validation. Scenarios were typically effects of bed reallocation, impact of high underlying occupancy, reductions in LOS (or variability), more beds or altered surgery schedules. Implementation issues were not widely discussed. Generic models appeared to be of similar design and useability.

4.2.3 Surgery

Jun et al (3) found Harris (54) examined various combinations of doctors and operating timetables, achieving reductions in bed numbers. Currie et al (55) (and Kwak et al (56)) modelled operating room utilisation, finding required numbers of operating rooms and recovery beds. Kutzdrall et al (57) simulated a theatre and recovery room to assess utilisation levels with different scheduling policies. Olson and Dux (58) found an 8th operating room was not required. Murphy and Sigal (59) and Fitzpatrick (60) examined the throughput implications of different operating theatre scheduling policies.

Longo and Masella (61) discuss a benchmarking study of operating theatres in eight Italian hospitals. The study compares key elements of the different services and found that processes can be split into four types: core, support, network and management. Key processes are: transportation, reception, preparation, induction and positioning, (where is the operation?), post op procedures, equipment cleaning, theatre cleaning, management of medical aids, linking to external services and laundry.

Lovejoy (62) discusses the difficulties in scheduling capacity expansion, and identifies three stakeholders: patients, surgical staff and hospital management and three performance criteria: wait to get on schedule, start time reliability, hospital profit. Different scheduling rules and techniques are modelled using mathematical formulations. Some evidence of implementation potential.

4.2.3.1 Surgery: Generic models

Blake et al (63) built a "generic" simulation model used in four hospitals in Toronto, Canada. It covers surgical patient flows from admission, through operating theatre back to beds and discharge. Operating theatre lists are developed for each day. Key characteristics are surgeon, service, age, sex and procedure. Key constraints are beds, nurses, operating theatre capacity and doctors. The model was validated against historic activity levels in beds and the operating room. Validation issues prompted further investigation by management, confirming operating room practice was different to theory (example of open box validation). The model was used to aid operating theatres reducing from 14 to 13 at one site, adequacy of resources, managing increased cardiac surgery and number of beds in holiday period.

4.2.3.2 Surgery: Specific models

Lowery (64) discusses a surgery simulation model in America to examine whether a hospitals operating suite could be reduced. Coverage was surgery only. Key factors were generation of modelled schedules accounting for specialty, operating room, DOW, arrival time and block start/stop times. Surgery times are sampled from history by specialty/surgeon, adding clean up time. Surgery downtime (due to delays (staff, patient, equipment) also modelled (80-85% typical availability). Modelled throughput was tested against actual by specialty. Results were discussed with surgeons. A baseline was generated and alternative schedules, extra time and case time reductions were modelled. Hospital policy changed, so proposals were not implemented.

Centeno et al (65) discuss a simulation model of a radiology department in America of operating room requirements, plus pre/post op. Data was collected on procedures, times, probability of cancellation, arrival patterns and returning patients. TOD and DOW arrival patterns were generated. Personnel, equipment and supply cost were modelled. Performance measures include Operating Room idle time, number of procedures, waits for OR, costs. Nothing on validation. Scenarios were on reduced support, extra ORs and different schedules. Nothing on implementation.

Ramis et al (66) describe a simulation model of ambulatory surgery in Chile. The objective was to increase throughput. Coverage is pre-operation examination and prep, into operation and then post op recovery and support. Resources modelled are beds by area and staffing. Process times for different types of procedure were agreed with surgeons. Validation was through discussion and demonstration and against historic data. Scenarios included extra patient prep areas. Not clear whether implemented.

Kwak (67) describes a simulation model of an operating room in America. Coverage is of the surgery and recovery suite. Patients are categorised by major/minor and specialty. Process times and variability in the OR and recovery rooms are generated from hospital logs. Validation techniques were unclear. Scenarios were around scheduling rules, testing against the baseline hospital policy of randomised allocation. Alternative strategies include long recovery times first, longest surgery first, patient categorisation. All managed strategies were found to be improvements on baseline. Hospital management chose and implemented one of the strategies

Wright (37) describes a surgical bed simulation model for Lancaster Health District. The objective was to assess a potential reduction in surgical beds. Beds were split into hospital, specialty and type (gender, children). Operating theatre sessions were collected (by specialty, major/minor, day, am/pm). Historical data was collected – emergencies/electives per day, LOS, pre and post operative LOS, sex. Simulated theatre sessions are generated using hospital policy. Validation was against historical bed occupancy. Scenarios were around demand, theatre capacity, bed changes. The model was used by management to plan responses to bed cuts, no action discussed.

Bowers (68) discusses a series of simulation experiments to examine potential economy of scale benefits of expansion on surgery and beds. The authors obtained data from a district general hospital in England on admission rates, LOS, theatre time. Incorporating variability shows distributions of beds required and theatre usage, suggesting the capacities and scheduling rules needed under base case and expansion scenarios. Nothing on implementation, the model is perceived to be generalisable.

4.2.3.3 Summary: Surgery models

Surgery models generally model patient throughput through operating theatres and associated pre and post op processes. Key outputs are patient throughput and theatre utilization. Coverage is typically some combination of beds, pre operation prep, operating theatres, post op recovery and beds. Other key factors include theatre cleaning/turnaround times after each patient, staff availability and patient type (minor/major, specialty, procedure, gender/age etc). Techniques are typically simulation, plus some models using different theatre scheduling rules. DOW and TOD issues are often modelled, particularly for the surgery specific processes. Design is typically through consultation with local experts on the key factors. Data collection and validation is usually through computer systems, plus open box validation with local experts. Changes modelled include changes in scheduling policies, increases and decreases in theatre capacity and changes in the numbers of inpatient beds. There is only limited evidence generally on implementation, one instance of new scheduling rules, another of altered bed allocations. There is only one generic model.

4.2.4 Critical/Intensive care

Jun et al (3) found that Lowery (69, 70) and Lowery and Martin (71) developed models of critical care bed requirements which account for interrelationships with other hospital units and are validated with hospital data. Zilm et al (72) simulated a surgical intensive care unit to determine optimal number of beds and observed that high weekday demand means that high overall occupancy is impossible. Romain–Jacur and Facchin (73) used simulation to optimise number of beds and staffing.

The DH critical care review (74) suggests improvements to critical care services including improvements in data collection, bed management, critical care networks, admission/discharge guidelines, staffing policy, workload and care guidelines.

Plati et al (75) report a survey of intensive care provision in Athens (Greece). Critical care beds constituted 2.3% of the bed population. They found that when the ICU is full, patients are held in A&E, wards or post operative recovery wards. ICU staffing levels were 2.3 nurses per bed per day to cover all three shifts. Average nursing time per bed per shift was 6 hours. Shortfalls in registered nurses are made up with aids.

Kapadia et al (76) discuss a LOS predictor in a paediatric intensive care unit in America as a sequence of “Low”, “Medium” and “High” illness states generated from Patients Risk of Mortality (PRISM) scores. They find that a Markovian sequencing approach is a good predictor of LOS, and the model to be generalisable.

Southgate (77) discusses a literature review of intensive care provision. Issues include low access to beds (10% of referrals refused), particularly surgery, Intensive Care Society recommendations of a 1:1 nurse-patient ratio (requiring 7 nurses per bed), overuse of beds by “too healthy” patients, and those who are dying and gain no benefit. There is a shortage of lower intensity High Dependency unit beds.

Pirret (78) discusses the use of the Therapeutic Intervention Scoring System “TISS” to differentiate between intensive care and high dependency patients, which was found to be an effective triage tool.

Williams et al (79) conduct a literature review of critical care workforce planning. Key areas are critical care capacity, medical staff, nursing staff, allied health professionals, health care assistants, workforce calculations and developments, plus safety and the relationship with staffing levels.

4.2.4.1 Intensive care: Generic models

Costa et al (80) discuss a simulation model of ICU capacity to meet demand. The model examines flows of patients through the unit, by casemix, arrival pattern and LOS (using CART), numbers of beds and typical variability. Key factors identified by CART were admission status (elective, emergency), source (operating theatre, A&E, wards, hospital transfers, others), specialty and age to generate patient groups with similar needs. Validation was against actual data with high rates of accuracy. The model was run at two different hospitals, the key factors being numbers of beds on occupancy, deferral rate and transfer rate. The model was generic, to allow input of local casemix, admission criteria, priorities and LOS. No evidence of implementation.

Demire et al (81) discuss a simulation model to investigate allocation of surgery time and general beds (including ICU). Patients are allocated to specialty beds. Surgery patients flow out of, then back into, beds. Key factors for surgery include pre op prep, operation time and post op recovery. Performance measures are throughput, time in system and patients rejected for admission. Nothing on validation or implementation.

Ridley et al (82) discuss a method for grouping patient types in ICU, generated in one hospital using CART and tested on 3 hospitals. Dependent variable was ICU LOS. Independent variables were source (e.g. A&E), age and specialty code. Nine groups emerged of combinations of these factors, giving a good match in all three hospitals.

4.2.4.2 Intensive care: Specific models

Griffiths et al (83) discuss a simulation model of an ICU in Wales. Key resources modelled are beds and nursing staff. The model takes admissions by DoW and TOD from each route (Elective/emergency surgery, A&E, ward, other hospital, high dependency unit, X ray). LOS distributions for each patient type are modelled, generating nursing requirements. Costs of nurse rosters are compared using bank and agency nurse costs. Data on arrivals, los and nurses from computer systems was used to design and validate the model. The model was used to examine numbers of rostered nurses, plus scenarios on referral rates, outreach programmes, increasing demand. Optimal numbers of rostered nurses were generated and implemented at the hospital.

Cahill and Render (84) describe a simulation model of an ICU in America plus feeder and surrounding beds. Data was collected over a one year period on time/day of ICU admissions/discharges, diagnoses, LOS in ICU and surrounding units, transfers between units, ER activity, plus other data on delays etc. LOS on each unit was modelled by diagnosis, plus down times. Validation was using historic data on utilisation, discharges and LOS. Scenarios were different number of beds in each unit with outputs being utilization and service levels.

Bonvissuto (85) discuss a model of ICU bed requirements in a hospital in America expecting demand increases. Data was collected on ICU bed occupancy, diagnosis, LOS and transfers. Interviews were conducted with key personnel. The hospital advised on appropriate levels of intensive care, step down beds, and transfer criteria.

Ridge et al (86) describe a simulation model of an ICU in England. The objective is to calculate optimal number of ICU beds to preserve service levels to patients at lowest cost. Arrival patterns and LOS of emergency and planned patients were pulled from computer records, and process flows/prioritisation rules for each patient type were defined (no detail on process). A simple mathematical queueing model generated basic results, then a simulation model was built. Patient volumes, LOS, numbers of beds, and arrival rates by DOW (but not TOD) were generated from computer records. Key output was number/% of patients transferred due to lack of bed. This was validated against historical records. Scenarios included number of beds, patient prioritisations, emergency bed reservations, changed DOW policies. Results show that better scheduling of planned admissions could have significant benefit. Also HRGs do not effectively differentiate patients - authors suggest CART techniques. No evidence of implementation. The methodology has high generic potential

Kim et al (87) describe a simulation model of an ICU in China to assess if it had sufficient capacity (was it full too often and/or patients waiting for admission). A queueing model and a simulation model were built. Routes into ICU were wards, A&E, emergency theatre and elective theatre. Patients were split by specialty. Patient attributes were illness severity, age, LOS and probable outcome. Patient volumes, arrival rates and LOS were generated from each source. TOD/DOW issues were not modelled. Validation was not clear. The model showed the unit was not undersized, but management was suboptimal. The model is generalisable

Shmueli et al (88) describe a queueing model to optimise the number of beds in an ICU to maximise lives saved in an Israeli hospital. Potential health benefit is specified as dependent on waiting time for admission. Costs of ICU beds are compared to modelled values of health benefit to find optimal bed numbers. Validation was against computer data. Nothing on implementation. The technique should be generalisable.

4.2.4.3 Intensive care summary:

There was evidence of generic and specific models developed in intensive care. Key outputs were typically bed utilisation, and risk of bed unavailability. Coverage was typically the ICU linked to the feeder sources and out to lower intensity, or non intensive care beds. Techniques were typically simulation, with some use of queueing models. Design was usually through local discussion with experts. Key factors are patient mixes by different sources (e.g. surgery, A&E, wards, inter hospital transfers), specialty and potential health benefit, nursing requirements by skill level, beds, LOS. TOD and DOW issues were often included. Computer systems usually contained enough data for modelling purposes – a key issue being identification of groups of patients (often using CART techniques). Validation was usually against computerised historical data, with evidence of local 'open box' validation with experts. Scenarios included impact of expansion/contraction of beds/nurses, demand changes, costing models, optimal sizing of unit and DOW. Only limited evidence of implementation.

The limited research evidence suggests that generically designed models have similar designs, and similar chance of success to specific models.

4.2.5 Diagnostics

Jun et al (3) found that O'Kane (89) , Klafehn (90) and Coffin et al (91) improved patient flow in diagnostics labs through more effective staff allocations.

4.2.5.1 Diagnostics Generic models

Ramis et al (92) describe a generic simulation model of a walk in multidiagnostic clinic in Chile. The company wished to reduce patient time in the system in a cost effective manner, and generate a tool for 40+ laboratories. Key factors and resources were TOD demand and staffing profiles, staff groups, test specific rooms and equipment and staff/test specific service times. Results were validated numerically against actual data collections and with physicians/nurses. Alternative staff schedules were tested, and a better cost neutral configurations were identified. Implementation not clear, although a production model was generated for use by all clinics.

Berchtold (93) describes a generic simulation model of clinical laboratories. A department in Germany helped establish general principles and test data. Some discussion of specific vs generic, plus material on workcells, and the generic nature of a flexible laboratory simulation model. Key factors were defined to be equipment, staff, demand types and TOD/DOW profiles, work planning methodologies. A model was developed, which was validated successfully, although no implementation.

4.2.5.2 Diagnostics: Specific models

Couchman et al (94) discuss a simulation model of a clinical biochemistry lab. Increases in workload (from hospital wards and the community) had been observed and anticipated. The model showed the changes in working practices, new equipment, or extra resources required to keep response times acceptable. The authors performed pre simulation queueing analysis to assess potential impacts. A model was developed through interview and walks through processes with lab staff and managers, plus collection of timing data. Demand profiles by TOD and DOW from all sources were collected. Resources were equipment and different types of lab staff. Validation was against lab performance by TOD. The model was tweaked in consultation with lab managers. Scenarios included changes in working practice, likely future performance, new instruments and automated handling. Implementation was unclear.

Ramakrishnan et al (95) discuss a simulation model of a CT Scan area in America to model patient throughput and report generation time with a new digital imaging service. Process mapping identified key flows, and data was collected from computer systems and observation studies. TOD demand issues by patient type were included, key resources were radiologists, technologists and clerks. Validation was against computer records on patient throughput and report generation time. Scenarios included increased machine use and numbers of radiologists. Impacts on throughput and report generation time were found to be significant. Nothing on implementation.

Van Merode et al (96) describe a DSS for a hospital in the Netherlands, but designed to highlight generalised issues of managing and optimising laboratory workflows. Coverage is a multifunctional lab with numerous workstations (21 different types of test). Data was collected on demand profiles, process times and technicians. Workstations and technicians are modelled with different jobshop layouts to assess throughput.

O'Kane (89) discusses a generalisable simulation model of a diagnostic radiology department in Northern Ireland (i.e. x rays). Demand is from A&E, outpatient clinics, appointment patients, hospital wards (each is differently dependent on TOD). Key constraints are rooms, equipment, radiographers. Some patients need multiple tests. Rooms and radiographers need turnaround time after each patient. Inputs are patient arrival patterns, examination requirements, durations of examination, number and type of rooms, number of radiographers. Performance measures were mean, max, min of patients seen by source/day/week, waiting times and queues, staff and room utilisation. Validation was by comparison against a pilot study. Scenarios included numbers of radiographers, separating facilities by hospital department, room usage, demand changes, appointment timetable changes. Nothing on implementation.

4.2.5.3 Summary: diagnostics models

There was less material in this area than other hospital departments, however, generic and specific models were found. The problem was usually to maximise patient throughput, minimise patient waits and optimize resource utilization (e.g machines, rooms, staff). Coverage was typically of self contained diagnostics departments of two types – clinical laboratories and radiology departments. Technique used was usually simulation, but also some issues such as jobshop and workcell layouts and some queueing analysis. Design was usually through local discussion. Key modelled issues were patient demand by type, TOD, DOW, test requirements, staff by specialty/skill level, number of rooms, types of machine. There was usually enough computer data for black box validation, plus some open box validation to determine working practices etc and some observation studies. Scenarios included different test scheduling practices, staff scheduling, different numbers/types of staff, demand changes, appointment timetable changes, new machinery. Little evidence of implementation. Generic models appeared to model very similar processes to specific models with similar levels of success.

4.3 Modelling flows between the above departments, and whole system models

Moreno et al (97) discuss a generic hospital simulation model to show the movements of patients through a whole hospital, with interactions with human resources and interventions from hospital management. Discussion centres on design issues, choice of simulation technique and software, technical simulation issues, and issues of generalisability – e.g. how to account for different hospitals with different flows etc. Specific issues of data collection, validation and implementation are not discussed.

Jun et al (3) identify multi-facility simulation models conducted by Hancock and Walters (98), Swisher et al (99) and Lowery and Martin (71).

Pitt (100) describes a generic simulation modelling framework used with West Yorkshire health authority. It covered all aspects of acute health delivery. The project created a “shell” with features of ease of use, transparency, interactivity, flexibility and versatility and ability for validation. The case study focussed on bed usage and allocations and covered demographic issues, demand fluctuations, admissions, hospital ward configuration, LOS and Day case rates. This enabled projections of optimal number of beds in hospitals/health authority. Validation is against Trust data. Implementation is not discussed.

Dittus et al (101) discuss a simulation model to improve doctors work schedules. This paper acknowledges that doctors work in a multi tasked environment with multiple objectives – it defines generic activities and assess allocation of time between these activities. The model then generates schedules, which proved to be accurate reflections of the impact of these changes when they were made.

Harper (102) presents a framework for modelling whole hospitals. Key issues identified include: Representing complexity, demand uncertainty, variability, limited resources, consideration of function of the model – e.g. is it a planning tool, or a management tool? Work with a group of hospitals on a potential generic framework generated the following user requirements: Flexibility and versatility, ease of use, integration, validity, appropriate outputs. CART techniques were used to generate patient types. A PROMPT system was built using the proposed methodology and used in a hospital to estimate surgery, workforce and associated bed needs. Not clear to what extent implemented.

4.4 General lessons about design, validation and implementation of (hospital) simulation models

Jun et al (3) identify soft system methodology as a technique used by Lehaney and Paul (103) and Lehaney and Hlupic (104) to aid in determining level of detail, system boundaries and system activities in complex models.

Jun et al also identify cases where simulation has been combined with optimization techniques. The optimisation technique is used to generate system alternatives at a global level, which are then analysed in greater detail by the simulation model. This method has been used by Carlson et al (105), Kropp et al (106) and Kropp and Hershey (107). Butler et al (108) used a similar approach using quadratic integer programming followed by simulation modelling to model scheduling and bed assignment problems.

Barnes et al (109) discuss “successful” applications of simulation in healthcare including pre operation procedures, new hospital design (including cardiology services, peri-operative services, imaging services and obstetrics) and outpatient design. Key success factors were identified as “selling” simulation, involving clients in the process and ensuring model transparency through use of user friendly software.

Standridge (110) proposes numerous key success factors when building simulation models. Issues include analysis of large data sets, often from multiple sources, for model inputs, TOD, DOW and seasonal demand issues, high variability in model outputs. Acceptance criteria include: model has more value than spreadsheet models, concepts of randomness and variability are explained, model builder is a member of the project team, model supports the information requirements of the team, model covers the key system components, build and report results of prototype model asap.

Haraden (111) notes numerous experiences of improving patient flow in many US and UK hospitals. Key lessons included: look at the whole system, not isolated units, understand natural and process variation in the early stages. Successful interventions include rescheduling elective procedures, planned patient discharge, extending the chain of care. Better flow can lead to improved outcomes and safety, greater staff/patient satisfaction and improved financial performance.

Lane (112) draws some lessons around client involvement in model building following an exercise in an A&E department. Key themes are: 1. Communicating the purpose and benefits of model building; 2. Dealing with aggregation; 3. Obtaining "ball park" estimates for key parameters where no data exists; 4. Dealing with busy professionals; 5. Creating ownership and confidence – have the sponsor act as advocate for the model; 6. Walking the system – getting a real sense of what goes on.

Hancock et al (113) discuss issues of staffing levels in units where daily workload is uncertain (e.g. A&E, diagnostics labs). They discuss various work completion policies in comparison to variability in demand and staff capability and illustrate impact on staffing, productivity and cost. Staffing models are generated.

Harper and Pitt (114) discuss issues of designing and implementing models/projects in the NHS. They identify the following issues: 1. Scale, complexity and change – NHS is Europes biggest organisation, with multidimensional issues – changes in demography, social issues, organizations, politics, strategy, technology, individual differences; 2. Diversity of provision – every local provider is different; 3. Buy in and credibility; 4. Conflicting objectives – e.g. managers vs clinicians; 5. Data issues – NHS data is rubbish. They propose a nine-point project life cycle. 1. Form steering group; 2. conduct feasibility study; 3. decide level of detail; 4. select appropriate tools; 5. gather information; 6. assess data quality; 7. design for wide use; 8. review project and foster relationships; and 9. promote results. Typical issues include involving end users, build credibility, politics and allocation of resources.

Lowery (115) identifies key aspects of simulation projects. Model building – keep model as simple as possible. Data collection, setting assumptions and documentation. Validation – open and closed box. Report results as simply and as early as possible. Compare actual results post implementation with model predictions.

Robinson et al (3) discuss the issue of model reuse. Pidd presents a spectrum of reuse, from code scavenging, through function reuse and component reuse up to full model reuse. Issues of model validity/credibility and cost are important. Nance presents three further dimensions: representational artefacts, object granularity and levels of organisational commitment. He discusses the key benefits, obstacles and pitfalls to reuse. Taylor discusses three levels of reuse – reuse of basic modelling components, up to reuse of subsystem models to reuse of similar models. Paul proposes a "G2R3" approach – with a problem, you "grab and glue" old ideas/model, run them, if satisfactory use them, otherwise reject, retry and round the circuit again.

Oses (116) discusses component based simulation and concludes it has potential benefits if organisations ensure systems are in place to ensure trust, support component documentation and component access and develop ways to share benefits between component developers and model developers.

5 Summary

5.1 Generic vs specific

The discussion of what constitutes a generic model is complex and multidimensional. Based on evidence from literature and responses to an informal survey, a framework leading from ‘specific models’ all the way up to ‘generic principles’ has been defined, and is based on the key dimensions of transportability and abstraction. Other factors in defining ‘genericity’ include software issues and levels of code/model reuse.

Considering key issues and potential success factors further illustrates the multidimensional issues when comparing generic and specific models. Twenty one key issues to compare generic and specific models emerged from the email survey and literature review. There are obvious differences between the models on these issues, but also perhaps a surprising amount of similarity between generic and specific models on many of them.

5.2 Modelling flows of emergency patients in individual departments

There is much evidence of simulation models developed in each of the key areas of acute hospitals that deal with emergencies – A&E departments, bed management, surgery, intensive care and diagnostics.

A&E model designs usually focus on time of day and day of week demand issues, issues of staff availability in A&E, changing working practices, physical constraints such as cubicles and whole system issues such as diagnostics and bed management. Key outputs are typically patient time and lengths of queues in A&E and utilization of key resources such as cubicles and staff.

Bed management models typically examine the impact of variability in demand by day of week and source, often by specialty to show the likelihood of surgery cancellations and/or ‘trolley waits’ in A&E. Key resources are typically beds (staffing is usually not modelled) Time of day issues are typically not considered. Key factors are average and variability of Length of Stay by day of week. Key outputs are typically average occupancy and number of ‘service failures’ – cancellations and trolley waits

Surgery models tend to concentrate on the requirement for beds pre and post surgery, plus preparation issues, surgery time and post operative recovery. Key constraints are inpatient beds, pre and post op trolleys/beds, theatre time and required staffing in theatre and pre and post op. Theatre scheduling issues are often discussed, with scheduling algorithms sometimes attempted. TOD and DOW are key factors. Key outputs are usually patient throughput and utilization of beds, surgery etc.

Intensive Care models tend to focus on requirements for beds and specialist nurses. TOD and DOW issues are key particularly in predicting demand. Key routes in are typically emergency and elective surgery, A&E, wards and other hospitals. There are often problems with discharging patients into lower dependency beds where appropriate. Costs of specialist beds and nurses are often key. Key outputs are utilization of beds and nurses, patient throughput and risks of non admission of patients.

Diagnostic models tend to be of two types, clinical laboratory models (e.g. blood tests) and radiology models. Both have similar features – TOD/DOW demands, staff skill mixes to do different types of test, equipment availability and room availability. There are often issues around staff multitasking and working practices and batching of tests. Key outputs include patient waiting time and throughput and utlilization of staff and equipment

Across all the above modes are similar features of deign, validation and implementation. Design is typically through discussion with local experts (a slight exception being bed management which rightly or wrongly appear to be more intuitive and less requiring of expert opinion). A common approach to design is process mapping. Data collection is typically either through computer systems or observation and consultation – and often both. Validation is typically a combination of techniques – comparison against historical data and discussion with local experts. Implementation is surprisingly rare – the exception rather than the rule. There are generally no reasons offered for this – in most cases there appeared to be good engagement with the local stakeholders in the design, data collection and validation stages – lack of implementation perhaps indicates that this is the hardest part of most projects as it requires a change in working practices or cutting of costs.

Overall, there have been examples of successful models in every department that deals with emergency patients. There is a large consensus about the key issues and resources to be modelled and key outputs.

5.3 Modelling flows between departments

There are some examples of attempts to model whole hospitals. However the published literature tends to focus on what we have described as flexible "generic frameworks" rather than "off the shelf" generic whole hospital models.

When considering the individual department models discussed above, there are some common themes in terms of connection to other departments.

A&E departments often include the effects of bed management in terms of the 'wait for bed' process, and the impact of diagnostics in terms of patient waits for X Ray/blood test results. However, this is usually modelled as the impact of these processes (e.g. as capacity unconstrained time distributions), rather than capacity constrained detailed submodels.

Bed management models usually model other departments as demand inputs – for example admissions from A&E, direct emergency admissions and patients pre and post surgery

Surgery models usually have demand inputs from inpatient beds, ICU, A&E or direct emergency admissions, and require available inpatient beds to discharge patients from surgery into.

Demand inputs into ICU are usually from elective/emergency surgery, A&E, direct emergency admissions and wards. Again, the ICU typically needs lower intensity inpatient beds to discharge patients into.

Finally, diagnostics models typically have demand inputs from inpatient beds, outpatients, A&E and community sources (e.g. GPs). Immediate discharge is assumed.

All the above models have TOD/DOW considerations for demand and discharge

Overall, there seems no reason why these models could not be joined together into a multidepartment model using the above knowledge about the inputs to and outputs from each individual department model.

5.4 General lessons on application of simulation in hospital

Some key themes emerged on the issues of applying simulation in the NHS. These were:

Working with clients

- Selling simulation is a challenge;
- Soft system techniques can help scope and design the model;
- Get the clients as involved as possible;
- Describe the issues generated by variability of demand and processes;
- Try and create an integrated team, of which the analyst is one part;
- Keep the momentum up – keep reporting progress at short intervals;
- Respect the fact that clients are busy professionals;
- Be clear about the objectives of the model;
- Be clear about how the results should be presented;
- Try and work in an implementation team;
- Ensure some validation takes place with the clients.

Modelling issues

- Make the model as transparent as possible;
- Optimization techniques can be effectively combined with simulation;
- Make the input data as accurate as possible, but don't be afraid to use national, or 'ball park' guesstimates where necessary;
- TOD and DOW is usually important;
- "Walk the system" – it is always worth knowing what you are modelling;
- Scale – scale and interconnectivity are key issues in the NHS;
- Diversity of provision – each local provider is different;
- Ensure that model is validated as far as possible;
- Consider questions of model reuse.

5.5 Comparison of success of specific and generic models in hospitals

In each of the individual department models discussed above there were examples of 'generic' and 'specific' models. In each case there were no clear design differences between generic and specific models, no real differences on data collection or validation techniques, and no clear differences in the chances of success and implementation.

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