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What is a 'generic' hospital model?—a comparison of 'generic' and 'specific' hospital models of emergency patient flows

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Abstract The paper addresses the question in the title via a survey of experienced healthcare modellers and an extensive literature review. It has two objectives.

1. To compare the characteristics of 'generic' and 'specific' models and their success in hospitals for emergency patients
2. To learn lessons about the design, validation and implementation of models of flows of emergency patients through acute hospitals

First the survey and some key papers lead to a proposed 'spectrum of genericity', consisting of four levels. We focus on two of these levels, distinguished from each other by their purpose. Secondly modelling work on the flow of emergency patient flows through and between A&E, Bed Management, Surgery, Intensive Care and Diagnostics is then reviewed. Finally the review is used to provide a much more comprehensive comparison of 'generic' and 'specific' models, distinguishing three types of genericity and identifying 24 important features of models and the associated modelling process. Many features are common across model types, but there are also important distinctions, with implications for model development.

Keywords Generic · Specific · Emergency · Hospital · Discrete event simulation

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1 Introduction

The primary motivation for this paper was the experience of one of the authors (AF) who had overseen the development of a 'generic' Accident and Emergency (Emergency Room in the US) Discrete Event Simulation (DES) model. This model proved to be a valuable tool in the drive to improve the performance of hospital Accident and Emergency (A&E) departments in England, (Fletcher et al. [1]) and we were interested to see whether this 'generic' approach could be extended to a whole-hospital simulation, in the first place for emergency patients. In addition to the value of improving performance for emergency patients, our hope is that many of the lessons learned for this important subgroup of patients and subsection of hospital departments will also shed light on the broader question of a 'generic' model for all hospital patients. In particular we note the coverage of hospital departments used by emergency patients is quite wide, and models of these departments will need to include the impact of elective patients and of a wide set of hospital departments.

Healthcare systems such as the NHS typically run many hospitals with similar objectives, in the face of broadly similar demands and resources. Hence in principle, 'generic' hospital models suggest a potential for understanding general problems faced by hospitals and the potential general solutions to improve service delivery.

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

Enter the OR modeller who aims to represent a situation in sufficient detail for decision making, but who is happy to use whatever is available that is good enough to improve understanding and aid decision making. If he/she is willing to contemplate fitting a mathematical formula as an adequate fit to the problem, why not use an existing model, especially if it can be tailored to the particular problem? Whilst such a transportable hospital model does not strictly qualify as ‘generic’ in the two senses above, they are nevertheless qualities to which it can aspire.

This paper reports the results of two 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) 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 research objectives of these exercises were:

1. To compare the characteristics of ‘generic’ and ‘specific’ models and their success or otherwise in modeling the flow of emergency patients in acute hospitals;
2. To learn lessons about the design, validation and implementation of these models with a view to the future development of a ‘generic’ hospital model for emergency patients.

The remainder of this paper is organised as follows. Sections 2 and 3 describe the email survey and literature review process respectively. Section 4 addresses objective 1 and presents an initial clarification of the term ‘generic’ based on the email survey and key papers from the literature review. In particular ‘generic’ models are compared with ‘specific’ models, and four levels of ‘genericity’ are defined. Section 5 uses the literature review to focus on objective 2. General lessons are highlighted and ‘generic’ models are contrasted with ‘specific’ models for 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 development of hospital simulation models. Section 6 returns to objective one in the light of the literature review. It proposes a further sub-division of ‘generic’ models, in particular highlighting their purpose. This enables a systematic comparison of key factors between ‘generic’ and ‘specific’ models. Finally Section 7 draws conclusions and indicates the direction of future work.

2 Email survey of experienced healthcare modellers

Our interest in the topic of ‘generic’ hospital models coincided with the 2005 annual meeting of ORAHS at Southampton University. Discussions with participants indicated a high level of interest in the topic, plus a variety of experiences and views. We followed up with an email request to around twenty experienced healthcare modellers in the group, plus a small number of OR practitioners in the Department of Health asking:

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 can be drawn from these examples about the value of developing generic models and associated challenges?

The quantity and quality of the responses was excellent, reflecting the importance of the issues to the interests and experiences of healthcare modellers. Responses were received from 20 modellers (see Acknowledgements for the respondent list), ranging from a half page to a 14-page discussion note! These responses anticipated many of the issues identified in the literature review, and also provided extra valuable insights and examples.

3 The literature review process

3.1 Stage 1

The search started with papers identified by a fellow researcher, Murat Gunal, in his PhD literature review in a related research area [2]. Forty three of these papers were of particular relevance to our objectives, including an extensive review of hospital simulation models by Jun et al. [3], in 1999. These papers referenced a further 350 potentially interesting papers, in addition to those referenced by Jun et al.

3.2 Stage 2

In order to focus on the defined objectives we prioritised papers by subject matter (based on the paper title), as shown in Table 1.

Our review then concentrated on papers in categories1–3. The extent and content of papers and books in these categories were sufficient to cover our objectives. Specifically, they provided extensive coverage of models of emergency care provision in and across hospital departments, plus lessons about building and implementing DES models in hospitals and elsewhere. In addition they provided many examples of ‘specific’ and ‘generic’ models.

Searches for the category 1–3 references found around 100 of the 250+ in the Lancaster University library. Many papers were from more obscure conference proceedings or journals that were not immediately available. These papers covered the objectives well.

Table 1 Prioritising literature search papers

Priority	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

3.3 Stage 3

In order to check that no recent relevant papers had been missed, the journals which had published the 100 papers were 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 to complement a key review of hospital simulation models by Jun et al. [3] in 1999. This search identified 15 extra category 1–3 references. In total, copies of 105 papers and ten books were obtained.

3.4 Stage 4

Once copies of all the references were examined, some were rejected as being not relevant enough to the objectives. Combining these papers with the relevant papers from Jun et al. [3] generated our final list of references.

4 Preliminary definitions of 'generic' and 'specific' models

To help set the context for the literature review, we attempt an early definition of 'generic' and 'specific' models using papers that specifically address this issue, the survey and our own personal experience in conducting OR projects. These sources indicate that the term 'generic' has meaning in terms of: (i) model abstraction and transportability, (ii) software and programming language, and (iii) model reuse.

4.1 Model abstraction and transportability

In general terms Lowery [4] asserts that a model should be general, flexible, intuitive and simple, and include default values for system parameters. Sinreich et al. [5] discuss three levels of genericity—the most generic being highly abstract models covering any system and scenario, the least generic being models of one specific system. In the middle are models of any provider of a similar process. The responses to the informal survey generated one extra level. Using the key dimensions of abstraction and transportability we therefore propose four broad types of model.

Level 1 A broad 'generic principle' model—e.g. a generalised theoretical queuing model. These models are not setting/industry specific.

Level 2 A generic framework that could be developed into a toolkit. For example, healthcare is characterised by issues of waiting, staff and equipment availability, beds, theatre time etc. These issues could be grouped into a theoretical healthcare modelling framework or toolkit with modules that represented these generic processes. Combined with local knowledge and input data, this toolkit could enable the user to generate a locally specific model. For example, the toolkit might contain a generic operating theatre. This could be adapted by the user to generate a specific operating theatre. It could also be used to illustrate general principles as in 'level 1' models. For example, it could show that operating theatres of certain throughputs need a certain number of beds to support them.

Level 3 A setting-specific generic model. For example, a generic model of an A&E department, or an outpatient department. Such a model could be used for general insights into the issues faced in delivering those services, and potentially also for multiple use by any providers of the same service. The model structure is unchanged, and changes in input data would be used to represent different providers.

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

These levels of genericity are summarised in Fig. 1 (using A&E as an example)

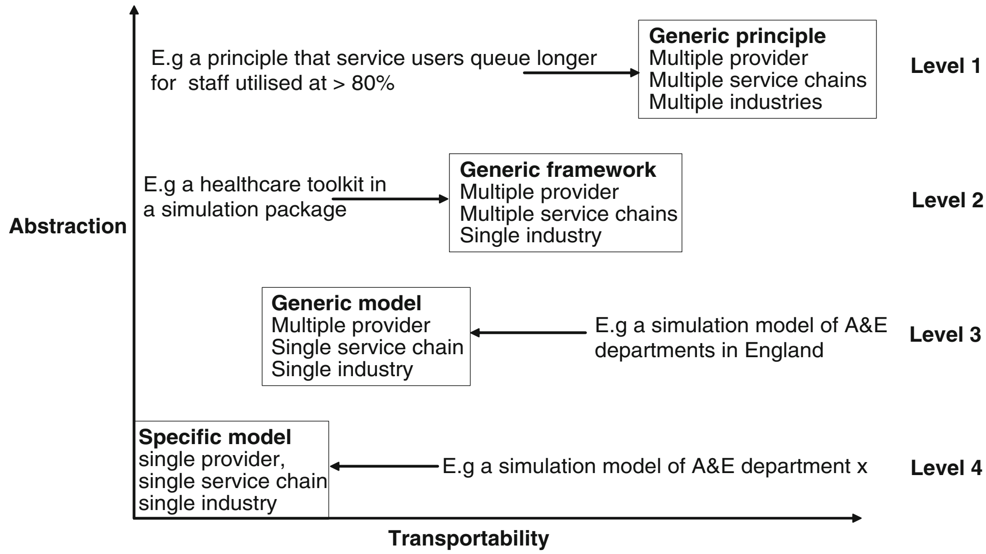

Fig. 1 The spectrum of genericity

4.2 Software and programming issues

Some responses to the survey suggested an alternative viewpoint—to consider modelling in terms of a software/ programming dimension:

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

Interestingly, consideration of this dimension did not arise in detail in the literature search apart from brief consideration in Robinson et al. [4].

4.3 Model reuse

Robinson et al. [6] discuss a spectrum of reuse, from "code scavenging" up to full model reuse and weigh these considerations against development cost. They propose a cycle of "grabbing and gluing" old ideas/models/pieces of code, running them, using if workable, otherwise rejecting and retrying. The key benefits of model reuse are identified as time, cost and consistency of output; obstacles being extra time/cost on projects to support future reusability, plus systems architecture issues. Significant pitfalls are around required levels of abstraction, and "force fitting" inappropriate models.

Further material on the general question of model reuse is also available from the military field—see Steele et al. [7] initially.

4.4 Generic and specific models—initial summary

For the remainder of this paper we focus on 'generic' according to model abstraction and transportability as defined in Fig. 1, and in particular on level 4 (specific) and level 3 (generic) models.

Figure 1 implies that the only difference between these two types of model is the design objective of transportability. In fact there many more dimensions beyond transportability on which it is possible to compare generic and specific models. For example, the authors' work on development of a generic A&E model [1] showed that fundamentally similar models might be used for distinct purposes. In particular the A&E model was developed as a national model that could identify and improve understanding of the key issues facing A&E departments. However it was subsequently used as a consultancy tool to aid struggling hospitals to improve their A&E departments.

A key objective of the literature search is to identify a wider set of dimensions on which to compare generic and specific models. We will return to this question in section 6, after the literature review.

5 Modelling flows of emergency patients in acute hospitals

This section first summarises the key lessons learnt from the literature review of generic and specific patient flow models through the following hospital departments:

- A&E
- Bed Management
- Surgery
- Intensive Care
- Diagnostics

Each section (5.1–5.5) starts with an introduction, which draws mainly on the Jun et al. [3] survey of DES in health care modelling. Whilst this survey did not use a generic/specific distinction it nevertheless provides an excellent starting point for each section. Subsequent sub-sections then examine the range of generic and specific models in detail, before summarizing the evidence.

For each model, an attempt is made to summarise the findings in the key project stages of initiation, design and build, data, validation and implementation.

In the validation stage, the broad categorisation suggested by Pidd [8] is used. He suggests two key validation techniques—"black box" and "open box" validation. Black box validation is where the model output is numerically tested against known characteristics of the system. Predictive accuracy is important. Open box validation is a critical assessment of the variables and relationships in the model. Performed in partnership with experts on the system being modelled, it generates mutual agreement that the model accounts for the key 'real world' issues. Both validation techniques were used here.

Section 5.6 then reviews material on modelling flows between departments.

5.1 A&E

5.1.1 A&E—introduction

There has been a long history of attempts to model A&E departments and Jun et al. [3] in 1999 identifies numerous applications of DES in A&E departments. The key output in all these papers [9–23] was patient time in A&E. The models examined the impact of a range of changes to practice in A&E and linked departments (e.g. diagnostics, critical care). These included patient routings, working practices, staffing levels and workforce scheduling algorithms. This review indicated the potential for insight against our two key objectives. The rest of this section on A&E describes the findings in detail for generic and specific models from recent papers.

5.1.2 A&E—generic models

Fletcher et al. [1] describe a centrally developed DES model to identify the key barriers to delivering the national target in England for 98% of A&E attendances to be completed within 4 h. They developed generic patient flows, required resources (staffing) and process times for each A&E process. The impact of diagnostics and bed management was modelled. Validation was against a national survey of A&E patient flows. The model was used nationally with key stakeholders to identify key issues and high impact interventions. The model was then used locally with hospitals struggling to meet the A&E target. The process of using a centrally developed generic model locally was described and discussed.

Sinreich et al. [5] discuss a generic A&E simulation model. They draw on Lowery [4] to assert that models should be general, flexible, intuitive and simple, and include default values for system parameters. The paper discusses three levels of genericity. Their model is aimed at the middle level—applicable to numerous A&E departments. By observing five different A&Es, five key patient types were identified and generic process charts were developed. Mathematical modelling suggested that a simulation tool based on a unified process was possible. Patient arrivals are modelled by time of day (TOD), grouped by testing requirements. Validation and implementation are not discussed.

Miller et al. [24] discuss a generic simulation modelling approach to Emergency Departments (EDs) using a reusable generic simulation framework—EDSim. They draw on case studies in America to discuss typical modelling interventions. EDSim can investigate issues such as discharging policy, overall capacity, lab processes, demand rises etc. Validation is not discussed. The 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. [25] describe a model that combines Linear Programming (LP) with DES to reduce staffing costs in an ED. They define generic patient flows and service time distributions for nurses and doctors at each process. Inter-arrival times of patients are estimated by TOD, and optimal resources and shift patterns are generated using LP for different demands. Validation methods were not clear. The paper suggests a particular ED, but results are presented as generic. Implementation is not discussed.

5.1.3 A&E—specific models

Takakuwa et al. [26] discuss a DES model of an ED in Japan. Coverage includes A&E processes, plus surgery. It is unclear how bed availability for surgery is modelled. Patients are grouped by type (ambulance, walk ins) with assigned routes. Resources include clerks, treatment cubicles, medical staff, nurses and diagnostic rooms. It is unclear how TOD and day of week (DOW) are modelled. The modelled outcomes are "congestion factor" and total patient time under different scenarios (e.g. staffing, beds etc). There is no discussion of validation techniques or implementation.

Blasak et al. [27] discuss a DES 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 waits for beds. Patients are categorised by arrival time, type (walkins, ambulance, direct) and urgency.

Processes/resources were diagnostics, staff (doctors, nurses, healthcare assistants), patient transport, cleaning, rooms, beds, 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 were reported to have "directed the change process". The Operations Director was involved and is one of the authors.

Rossetti et al. [28] discuss a DES model of an ED in Virginia, US to increase patient throughput and optimise staff utilization by altering staff schedules. Design covered patient groups, doctors and nurses, beds and diagnostics. TOD and DOW patterns were modelled. Validation included computer system and on site data collection, local discussions of model design and results, and comparison with waiting time data. Site data collection included patient arrival and wait characteristics, staff service times, and transport and routing times. Staffing schedules were compared for effects on throughput and staff utilization. Implementation was not discussed.

Baesler et al. [29] discuss a DES model of an ER in Chile. Demand increases were expected. The model showed potential impact on (non admitted) patient waiting time. Doctors, rooms, paramedics, reception staff and testing were included. TOD and DOW were not obviously modelled. Validation was not discussed. Scenarios based on demand rises and capacity changes generated recommended staff levels. Implementation was not discussed.

Miller et al. [30] discuss a DES model of an ED in the US. A six sigma methodology generated potential improvements. A conceptual model was developed in Visio with clients. There is no discussion of model design or validation. Key improvements modelled included a changed discharge process, more beds, and improved testing. The key consultancy issue was defining scope with clients—20 design iterations were required. The model was reported to have been "handed over".

Wiinamaki et al. [31] describe a DES model at an ED in the US which required a new build to cope with extra demand. All A&E processes, clinical decision and admissions units are modelled. Validation was not discussed. Some recommendations were accepted—extra X Ray space, new triage and less acute beds.

Blake and Carter [32] discuss a DES study in a children's ED in Canada to help reduce waiting times for patients with primary care conditions. All key processes and personnel were included. Existing hospital data plus direct observation was used for data (particularly doctors multitasking workloads). Key outputs were total time and time to first assessment. TOD/DOW factors were modelled. Validation was against actual data. ANOVA modelling suggested doctor availability was key. A fast track minor stream was also modelled. The model supported implementation of new practices such as a fast track and a new clinic.

Badri and Hollingsworth [33] discuss a DES of an ER in the UAE. ER activities were included for five patient groups (but nothing on diagnostics or bed waits). Service times at each process were generated. Medical, pharmacist and admin staffing levels were modelled, plus ER beds. There was no obvious recognition of TOD/DOW demand, but staff shift patterns were incorporated. Validation was through interviews with local experts and comparison of total time data. Changed patient priorities, diversion of minor patients and staffing profiles were modelled, which generated recommendations which were implemented (and monitored).

Lane et al. [34] discuss a system dynamics (SD) model of an A&E department, (including bed management) in England. The objective was to reduce patient time in A&E (particularly admitted patients). SD was chosen for a more strategic system perspective. The model included all A&E processes (including testing), bed management (including electives) and doctor utilization. TOD was included. Validation was through discussion with local experts and comparison with data. Scenarios included changes in bed capacity and demand patterns. Implementation was not discussed.

Komashie and Mousavi [35] describe an A&E DES model in England to understand the drivers of patient time (average and variability). Scope included the Medical Admissions Unit and diagnostics. A&E doctors and nurses were modelled. TOD was modelled. Process times were generated through observation, plus computerised data. Validation was through demonstration to key experts and comparison with Key Performance Indicators (KPI's). Scenarios included adding cubicles or staff, and improved admission processes. Significant potential improvements were observed, but implementation is unclear.

Samanha et al. [36] discuss a DES model of an American ED. Objectives were to show the ED process and bottlenecks and assess improvement options to reduce patient time in the ED. Coverage was the ED, including impact of testing and bed availability. Data on arrival and process times was collected through observation. ED resources modelled were rooms, doctors and other staff. Validation was primarily 'open box'. Scenarios included changed pathways, ED resizing, and fast-tracking of patients. The model found that process changes would avoid the need for expansion. The results were implemented.

Mahapatra et al. [37] discuss a DES 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, and combined with interviews and observation. Patient flow through triage, assessment, testing, treatment and discharge/admission was modelled. The ED was split into three sections—Critical care for the most acute, and Intermediate/Alterna care for less acute. These, plus triage, diagnostics and follow-up treatment were all modelled. TOD and DOW were modelled. Validation was by open and black box methods. Scenarios showed that expansion of the fast-track area would improve throughput. Implementation was not discussed.

Gonzalez [38] discusses a DES model of an ED in Spain. Patient time and queue length are key outputs. Doctors and nurses are key resources, testing, assessment, treatment and waits for bed are key processes. Open and black box validation were used. Scenarios around staffing and patient routing were run. Implementation was not discussed.

5.1.4 Summary—A&E models

There is more evidence of specific A&E models than generic models. 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 include inpatient bed management, diagnostics and surgery modules, but the effects of these are often modelled simply as time distributions. Techniques are mainly DES, but there is some evidence of scheduling, queuing models and SD. Design is usually through discussion with local experts. Data collection is generally through computer records, but also occasionally through 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 there is evidence that generic and specific models have been used with similar success.

5.2 Bed management

5.2.1 Bed management—introduction

The Jun et al. survey [3] indicates that bed management models [39–48] concentrated on issues such as waits for bed (emergencies), cancellations (electives), misallocation of patients and occupancy/bed numbers overall, often by specialty. Simulation and integer/linear programming were the typical techniques used.

5.2.2 Bed Management—generic models

Bagust et al. [49] discuss a generic, spreadsheet based simulation model of emergency inpatient bed requirements at a hypothetical acute hospital. Notional emergency bed capacity was defined, and randomised admission rates per day and LOS around seasonal and DOW patterns were generated. Data from two hospitals were used for validation. TOD was not included. The KPI is risk of non admission of emergency patients. Validation techniques were unclear. Scenarios included growths in emergency demand, occupancy levels, LOS changes, resource pooling. Nothing was implemented—the model was developed as a discussion tool.

Nguyen et al. [50] present a generic model to generate an optimal number of beds in a unit, illustrating the balance between transfers, "refused" unscheduled admissions and unoccupied beds, i.e. the department must not overflow, nor remain too empty. The algorithm minimises the mean and standard deviation of each of these. The model was validated on surgery and medicine departments, and improved performance compared to current bed allocation methods.

Gorunescu et al. [51] discuss a bed management model using queuing theory. The model is validated on a hospital but is generalisable. By assigning costs of refused access, occupied and unoccupied beds, the model generates the optimal number of beds.

Mackay [52] discusses a generic model, useable at regional, hospital or specialty level in South Australia. Required data is patient type, occupancy and LOS. Patients were split into two types (e.g. short/long LOS) and daily/monthly occupancy rates are calculated. The model was validated on actual occupancy data, and the author suggests the model is generalisable.

Harrison [53] 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 US hospitals, implying different management practices.

5.2.3 Bed management—specific models

Harper and Shahani [54] discuss a DES model for an English hospital. Inputs included hourly, daily and monthly arrival and discharge rates, LOS and beds by patient "CART" category. "Refusal rates" were modelled (a bed is unavailable in the preferred unit). Validation was against a year's occupancy/refusal rates. Recommendations have been implemented, including bed requirements (allowing for variability), combining bed pools, patient categorisation and admissions policies.

Harris [55] describes a DES model of surgery ward beds (pre/post op). Surgery schedules by type of patient and consultant, and LOS and variability for each patient type were required. The model calculated average (and variability of) bed requirements. Scenarios included improved theatre schedules and bed management policies. Implementation was not discussed, although it was to be used in a South Wales hospital.

Dumas [56] describes a model in a US hospital to improve bed allocation and patient placing policies between specialties. Demand, the admission process, and inpatient patient movements through to discharge were modelled. Specialty level demand was generated and the process of assigning the demand to bed pools was modelled. LOS's are sampled from specialty level distributions. Admission and discharge profiles were by DOW. KPI's were occupancy and misplacements. Validation was through structured discussion sessions with bed managers. Numerous patient placement rules were tested, and better bed allocations by specialty were generated to reduce misplacements and standardise occupancy. Implementation was not discussed.

Vissers [57] discusses a bed allocation procedure by specialty in a hospital. The model took projections in demand and LOS to generate optimal bed allocations based on actual use. Implementation was not discussed.

5.2.4 Summary—bed management models

There is an even spread of published literature between generic and specific bed management models. Models can cover anything from a single specialty, to hospital level, 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 was commonly used, but often using spreadsheets and occasionally combined with LP/IP to determine optimal bed mixes by assigning costs of rejections and unoccupied beds. Key modelled factors were projected bed occupancy using patient arrival patterns (by type), LOS and known variability. Most models worked at the daily level. Most accounted for DOW, but most did not include TOD issues. Computerised data was usually used for design and validation. Scenarios were typically effects of bed reallocation, impact of different average occupancy, reductions in LOS (or variability of), more beds or altered surgery schedules. Implementation issues were not widely discussed.

5.3 Surgery

5.3.1 Surgery—introduction

In their review of papers describing surgery models [55, 57–65] Jun et al. [3] indicated that DES was the key technique used to examine the number of staff, theatres and beds required to achieve the required patient throughputs or "service levels" (e.g. reducing cancellations/waiting times), often using alternative scheduling algorithms.

5.3.2 Surgery—generic models

Blake et al. [66] built a "generic" DES model used in four hospitals in Canada. It covered surgical patient flows through admission, operating theatre, beds and discharge. Theatre lists were developed for each day. Key characteristics were surgeon, service, age, sex and procedure. Key constraints were beds, nurses, operating theatre capacity and doctors. The model was validated against historic activity in beds and theatres. Validation issues prompted further investigation by management, confirming operating room practice was different to theory. The model was used to justify theatres reducing from 14 to 13 at one site, adequacy of resources, increased cardiac surgery and beds in holiday periods.

5.3.3 Surgery—specific models

Lowery [67] discusses a surgery simulation model in America to examine a hospital's theatre capacity. . Key factors were schedules accounting for specialty, theatre, DOW, arrival time and block start/stop times. Surgery times were sampled from history by specialty/surgeon, adding clean up time. Surgery downtime (due to staff, patient, equipment) was also modelled . Modelled throughput was tested against actual throughput by specialty. Results were discussed with surgeons. A baseline was generated and alternative schedules, extra time and case time reductions were modelled. General hospital policy changed, so the proposals were not implemented.

Centeno et al. [68] discuss a DES model in US of theatre and pre/post-operation requirements. 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 included theatre idle time, throughput, waits for theatre, and costs. Scenarios were on reduced support, extra theatres and different schedules. Validation and implementation were not discussed.

Ramis et al. [69] describe a DES model of surgery in Chile. The objective was increased throughput. Coverage is pre-op preparation, operation and then post-op recovery and support. Modelled resources were beds by area and staffing. Process times for different procedures were agreed with surgeons. Validation was through discussion and against historic data. Scenarios included extra patient preparation areas. Implementation was unclear

Kwak [70] describes a DES model of a theatre in US. Coverage was of the surgery and recovery suite. Patients were categorised by major/minor and specialty. Process times and variability in the theatre and recovery rooms were generated from hospital logs. Validation techniques are unclear. Alternative scheduling rules and patient categorisation were tested against the baseline hospital policy of randomised allocation. All managed strategies were improvements. Hospital management chose and implemented one of the strategies.

Wright [40] describes a surgical bed DES model for Lancaster Health District. The objective was to assess potential reductions in surgical beds. Beds were split by hospital, specialty and type (gender, children). Theatre session data were collected (by specialty, major/minor, day, am/pm). Bed data included emergencies/electives per day, LOS (pre- and post-op) and sex of patient. Simulated theatre sessions were generated using current hospital policy. Validation was against historical bed occupancy. Scenarios included changes in demand, theatre capacity and beds. The model was used to plan responses to bed cuts.

Bowers [71] discusses a series of DES experiments to examine potential expansion of surgery and beds. Data was from a hospital in England on admission rates, LOS and theatre time. Distributions of required beds and theatre usage were generated, leading to recommendations for capacities and scheduling rules under base case and expansion scenarios. The model was felt to be generalisable. Implementation was not discussed.

5.3.4 Summary—surgery models

Surgery models generally model patient throughput through theatres and pre and post op processes. Key outputs are patient throughput and theatre utilization. Coverage is typically some combination of beds, pre-op preparation, theatres and post-op recovery. Other key factors include theatre turnaround times, staff availability and patient type (minor/major, specialty, procedure, gender/age etc). Techniques are typically simulation and/or scheduling. DOW and TOD issues are often modelled. Design is typically through consultation with local experts. Data collection and validation is usually through computer systems, plus open box validation with local experts. Scenarios included changes in scheduling policies, theatre capacity and inpatient beds. There is only limited evidence of implementation.

5.4 Critical/intensive care (ICU)

5.4.1 Critical/intensive care—introduction

The Jun et al. [3] review of models [72–82] indicated that ICU simulation models generally assessed the required levels of staffing and beds, which in ICU tend to be high cost. Demand patterns from different departments is a key factor, with waits for admission, and inappropriately long stays being the key patient focussed issues.

5.4.2 Intensive care—generic models

Costa et al. [83] discuss a DES model for planning ICU capacity. The model examines flows of patients through the unit, by casemix, arrival pattern and LOS, numbers of beds and typical variability. Key factors were admission status (elective, emergency), source (theatre, A&E, wards, hospital transfers, others), specialty and age. This generated patient groups with similar needs. Validation was against actual data. The model was run at two hospitals, the key factors being beds vs. occupancy, deferral rate and transfer rate. The model was generic, allowing local casemixes, admission criteria, priorities and LOS. There is no evidence of implementation.

Demire et al. [84] discuss a DES model to investigate allocation of surgery time and beds by specialty (including ICU). Key factors include pre-op surgery preparation, operation time, post-op recovery and beds. KPIs are throughput, time in system and patients rejected for admission. There is no discussion of validation or implementation.

Ridley et al. [85] discuss a method for grouping ICU patient types generated in one hospital using CART and tested on three hospitals. The dependent variable was ICU LOS. Independent variables were source (e.g. A&E), age and specialty. Nine groups emerged which fitted all three hospitals well.

5.4.3 Intensive care—specific models

Griffiths et al. [86] discuss a DES model of an ICU in Wales. Key resources are beds and nursing staff. Admissions by DOW and TOD from each route (elective/emergency surgery, A&E, ward, other hospital, high dependency unit, X ray) are modelled. LOS distributions for each patient type generate nursing requirements. Nurse roster costs are compared using bank and agency nurse costs. Data on arrivals, LOS and nurses was used for validation. The model examined numbers of rostered nurses, scenarios on referral rates, outreach programmes and increased demand. Optimal numbers of nurses were generated and implemented.

Cahill and Render [87] describe a DES model of an ICU in the US plus feeder and surrounding beds. Data was collected over one year on time/day of ICU admissions, discharges, diagnoses, LOS in ICU and surrounding units, transfers between units, ER activity and delays. LOS was modelled by diagnosis. Validation was using historic data on utilisation, discharges and LOS. Scenarios were different numbers of beds in each unit. KPIs were utilization and service levels.

Bonvissuto [88] discuss a model of ICU bed requirements in a hospital in the US. Data was collected on ICU 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. Nothing on implementation.

Ridge et al. [89] describe a DES model of an ICU in England to calculate optimal number of ICU beds to preserve service levels at lowest cost. Process flows and priority rules for each patient type were defined. A simple mathematical queuing model generated basic results, then a simulation was built. Patient volumes, LOS, numbers of beds, and arrival rates by DOW (but not TOD) were generated from computer records. The KPI was number/percentage of patients transferred due to lack of beds. This was validated against historical records. Scenarios included number of beds, patient prioritisations, emergency bed reservations, and changed DOW policies. Results showed that better scheduling of planned admissions could have significant benefits. There was no evidence of implementation. The authors claim the methodology has high generic potential.

Kim et al. [90] describe a DES and a queuing model of an ICU in China. Routes into ICU were from wards, A&E, and emergency/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 by route. TOD/DOW issues were not modelled. It is not clear what validation techniques were used. The model showed that the management was suboptimal. The authors claim the model is generalisable.

Shmueli et al. [91] describe a queuing model to optimise the size of an ICU in Israel. Health benefit was modelled as dependent on wait time for admission. Costs of ICU beds were compared to modelled values of health benefit to find optimal bed numbers. Validation was against computer data. Nothing is reported on implementation. The technique is claimed to be generalisable.

5.4.4 Intensive care—summary

There is evidence of generic and specific models in Intensive Care. KPIs were typically bed utilisation and risk of bed unavailability. Coverage was typically ICU linked to feeder beds and lower intensity/non Intensive Care beds. Techniques were typically simulation, with some use of queuing 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. Identification of groups of patients was key (often using “CART” techniques). Validation was usually against computerised data, with some ‘open box’ validation with experts. Scenarios included impact of expansion and contraction of beds and nurses, demand changes, costing models, optimal sizing of unit and DOW modelling. There was only limited evidence of implementation.

5.5 Diagnostics

5.5.1 Diagnostics—introduction

Jun et al. [3] only report on three papers [92–94] in this area, each of which uses simulation to examine the impact of staff allocations on patient throughput.

5.5.2 Diagnostics—generic models

Ramis et al. [95] describe a DES of a multidiagnostic clinic in Chile to reduce patient waiting times cost effectively across 40+ labs. Factors were TOD demand and staffing, staff groups, test specific rooms and equipment, and staff/test specific service times. Results were validated against data and with staff. Alternative staff schedules were tested, and better (cost neutral) configurations were identified. It is unclear whether the model was implemented.

Berchtold [96] describes a DES of clinical laboratories. A department in Germany helped establish general principles and test data. The paper discusses specific vs. generic issues, material on workcells, and the generic nature of a flexible laboratory simulation. Key factors were equipment, staff, demand types, TOD/DOW profiles, and work planning methodologies. The model was developed and validated, but it is unclear whether it was implemented.

5.5.3 Diagnostics—specific models

Couchman et al. [97] discuss a DES model of a clinical biochemistry lab to model increases in workload. The model showed the changes in working practices, new equipment, or extra resources required to keep response times acceptable. Pre-simulation queuing analysis assessed potential impacts. Design was through interview and process walking with lab staff and managers, plus collection of timing data. Demand profiles by TOD and DOW were collected. Resources were equipment and lab staff (by type). Validation was against lab performance by TOD and with lab managers. Scenarios included changes in working practices, likely future performance, new instruments and automated handling. It is unclear whether the model was implemented.

Ramakrishnan et al. [98] discuss a DES of a CT Scan area in the US to model patient throughput and report generation time with a new service. Process mapping identified key flows, and computer and observation based data was collected. TOD demand by patient type was included. Key resources were radiologists, technologists and clerks. Validation was against data on throughput and report generation time. Scenarios included increased machine use and numbers of radiologists. There was significant improvement potential on throughput and report generation time. Implementation was not discussed.

Van Merode et al. [99] describe a DSS for a hospital in the Netherlands, to improve laboratory workflows. Coverage is a multifunctional lab with numerous workstations. Data was collected on demand profiles, process times and technicians. Workstations and technicians were modelled with different layouts. Implementation was not discussed.

O'Kane [92] discusses a generalisable simulation of a diagnostic radiology department in Northern Ireland. Demand was from A&E, outpatient clinics, appointment patients, hospital wards by TOD. Key constraints were rooms, equipment, radiographers and turnaround times. Some patients needed multiple tests.. Inputs were patient arrival patterns, examination requirements and durations, number/type of rooms, radiographers. KPIs 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 data collection. Scenarios included numbers of radiographers, streaming by hospital department, room usage, demand changes, and appointment changes. Implementation was not discussed.

5.5.4 Summary—diagnostics models

There was less material in this area than for other hospital departments, but generic and specific models were found. Key issues were to maximise patient throughput, minimise patient waits and optimize resource utilization (machines, rooms, staff). Coverage was usually self-contained diagnostics departments of two types—clinical laboratories and radiology departments. The technique used was usually simulation, but there was also some other modelling concerning alternative layouts and some queuing 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. Validation was through computer data, some open box validation and some observation studies. Scenarios included different test scheduling practices, staff numbers, skill matching and scheduling, demand changes, appointment changes, new machinery. Little evidence of implementation was presented.

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

Jun et al. [3] identify multi-facility simulation models conducted by Hancock and Walters [100], Swisher et al. [101] and Lowery and Martin [74].

Moreno et al. [102] discuss a generic simulation of a whole hospital, with interactions with human resources and hospital management. Discussion centres on design issues, choice of simulation technique and software, technical simulation issues, and generalisability—e.g. how to account for different hospitals with different flows etc. Specific issues of data collection, validation and implementation are not discussed.

Pitt [103] 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, versatility and ease of validation. The case study focussed on bed usage and allocations and covered demographic issues, demand fluctuations, admissions, ward configuration, LOS and day case rates. The output was projections of optimal number of beds in hospitals/health authority. Validation was against hospital data. Implementation is not discussed.

Dittus et al. [104] discuss a simulation to improve doctors work schedules in an acute hospital. They acknowledged that doctors work in a multi tasking environment with multiple objectives, and their model defines generic activities and assesses allocation of time between them. The model generates schedules, which proved to be accurate when implemented.

Harper [105] 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, or a management tool? Work with a group of hospitals generated the following user requirements: flexibility and versatility, ease of use, integration, validity, appropriate outputs. CART techniques generated patient types. A system, referred to as PROMPT, was built using this methodology and used in a hospital to estimate surgery, workforce and bed needs. It is not clear whether the model was implemented.

In summary, the published literature suggests only a small amount of work in this area, and that generic models are more common than specific when considering hospital wide models. The design and coverage of the whole hospital models is dependent on the objectives—ranging from all aspects of healthcare delivery to models specifically focused on planning doctors schedules. Some validation of such models appears possible against actual data and also using open box techniques. There appear to be similar

Table 2 Key factors in generic and specific models—project initiation

Issue	Level 3A: generic model—central	Level 3B: generic model—multiple applicability	Level 4: specific model	Similarity
Scope	Depends on problem	Depends on problem	Depends on problem	***
Purpose	Some or all of the following: 1. To make general observations about the design and performance of a service. 2. To identify high impact interventions to improve the service 3. To build common understanding of the system amongst key stakeholders 4. To build greater understanding of the theoretical capability of the system	To be transportable enough to achieve some or all of purposes 1-4 in a number of specific local services. 5. To model the local system, and proposed changes, in detail	Some or all of the following: 1. To make observations about the design and performance of a local service. 2. To identify high impact interventions to improve the local service 3. To build common understanding of the system amongst key local stakeholders 4. To build greater understanding of the theoretical capability of the system 5. To model the current system, and proposed changes, in detail	**
Level of insight	Broad discussion of issues and potential high impact interventions	From broad discussion of issues to accurate and detailed local improvement strategies	From broad discussion of issues to accurate and detailed local improvement strategies	**
Level of accuracy	Possibly lower	Possibly higher	Possibly highest	**
Conflict with existing models	Addresses perceived/actual gaps in existing central models	May conflict with existing local models, or may have been designed to fill a perceived local gap.	Addresses perceived/actual gaps in existing local models	**
Target level of use	Centrally	In multiple providers	In a single provider	*

issues with implementation as with the single department models discussed earlier.

6 Generic models vs. specific models

Returning to the first objective of the research (to compare the characteristics of 'generic' and 'specific' models) we now revisit Fig. 1, in particular level 4 (specific) and level 3 (generic) models, and the two dimensions of abstraction and transportability.

Combining the literature review with the survey we propose a much more detailed set of twenty four dimensions which we group under five main headings: project initiation, design and build, data, validation and implementation. We also suggest that an understanding of the nature of 'generic' models can be better achieved if Level 3 models (as defined in Fig. 1) are split into two: 'generic' models designed for central use (level 3A) and 'generic' models designed for multiple local use (level 3B).

Using this structure we can compare and contrast the model characteristics in terms of the twenty four dimensions grouped by the five key project stages for models at levels 3A, 3B and 4. We also provides a similarity indicator for each dimension, in which *** means that there are no clear differences between any of the three model types, ** means that two of the model types are similar but one is different, and * means there are clear differences between all types of model.

Table 2 shows the key dimensions in **project initiation**. For generic models the *purpose*, and the *target level of use* must be very clearly defined with key stakeholders. For example, is the model to be designed for central use to provide general insights, or as a locally applicable model, or both? Realistic assessments of levels of *insight and accuracy* of the different types of model must be made before development. The requirement to clearly define *scope* is common to all three model types.

Table 3 shows the key dimensions identified for **model design and build**, the key differences are the possible extra step in the *design objective* of generic models to assess *appropriateness* for central and local use: and the *design process* of consulting central and local experts for generic models to model key common processes only, as some local issues may be too *detailed* for a generic model. As a result, some generic models may not be locally applicable. There is also potential in specific models to *represent local processes* through the model structure (rather than changing

Table 3 Key factors in generic and specific models—design and build

Issue	Level 3A: generic model—central	Level 3B: generic model—multiple applicability	Level 4: Specific model	Similarity
Levels of code/model reuse	Depends on previous work by the modeller or organisation, degree of knowledge sharing or availability of generic software code/modules	Depends on previous work by the modeller or organisation, degree of knowledge sharing or availability of generic software code/modules	Depends on previous work by the modeller or organisation, degree of knowledge sharing or availability of generic software code/modules	***
Design process	Working with central experts, plus local service(s)	Working with central experts, plus local service(s)	Working with local expert(s)	**
Representation of local issues	Not necessarily required in detail.	By changing data inputs, not model structure.	Potentially better representation—through model structure and design as well as input data	**
Appropriateness of use	Clearly defined systems and problems for which the model is applicable. Model may be adjustable to fit different problems	Need to clearly define when model can be appropriately used—i.e. when modification of input data is appropriate to model the problem.	Greater likelihood of local adjustment of model structure to fit the problem	**
Level of detail	Inclusive of common significant processes in multiple providers	Inclusive of common significant processes in multiple providers	Inclusive of significant (locally agreed) processes in the particular provider	**
Design objective	To model common processes in a range of providers.	To model common processes but ideally flexible enough to model some local process differences through input data	To model one local system. The local process may be similar to other providers, but not a design objective	**
User knowledge of structure and inner workings of model	If users have been involved in developing model, possibly high.	Initially low (local users weren't involved in design),	Local user(s) likely to have been involved in model build, so probably higher?	**

input data). This may lead to greater *user knowledge* of the model structure. There are no clear differences between any of the model types in the potential for *code/model reuse.*

In terms of **data**, Table 4 identifies the key issues. Differences lie in the types of *test data* used (e.g. national average data for and/or local data as well), and the possibility for specific models of extra *accessibility* to particular locally available data, or for making special collections. The level of *data quality* required is not specific to any of the three model types

Table 5 shows the key dimensions identified for **validation.** The differences are most marked between type 3A models and the other two types. For type 3A validation will be against 'average' data and will require that results are broadly accurate, whilst types 3B and four require validation against local data and a greater level of accuracy and granularity. *Validation* techniques (i.e. open or black box) are similar for the three model types.

Finally, Table 6 illustrates the key factors for **implementation.** The model, whatever the type, to be handed over to a user. If handover is required, *user capability and support* becomes an issue. Most demanding in this respect are type 3B generic models, where supporting numerous sites would require the user front end and documentation to be very clean and clear to reduce the requirement for site visits. In this case it would be particularly beneficial for the model to require no particular local *hardware/software requirements*.

A locally developed specific model (type 4) might imply a greater *local desire to use* it, but local politics are still a factor, and there is no evidence in the literature that specific models are more likely to be implemented. Type 3B generic models will have to prove to local management that they are

Table 4 Key factors in generic and specific models—data

Issue	Level 3A: generic model—central	Level 3B: generic model—multiple applicability	Level 4: Specific model	Similarity
Data quality	Depends on type of model/required accuracy	Depends on type of model/required accuracy	Depends on type of model/required accuracy	***
Data accessibility	Ideally easily accessible from standard operational systems	Ideally easily accessible from standard operational systems	Ideally easily accessible from standard operational systems. Extra local collections possible.	**
Test "starting" data	Possibly "national average", plus local examples and national estimates	Possibly "national average", plus local examples	Local historical data	**

Table 5 Key factors in generic and specific models—validation

Issue	Level 3A: generic model—central	Level 3B: generic model—multiple applicability	Level 4: Specific model	Similarity
Technique	"Open box" with national and local experts, "black box" with national/local data	"Open box" with national and local experts, "black box" with local data	"Open box" validation with local experts, plus "black box" with local data	***
Representation	"General" level only	A range of individual providers	One provider	**
Required accuracy	Depends on purpose of model	Depends on purpose of model	Depends on purpose of model	**
	Broad accuracy against average data may be enough	Medium to high levels of accuracy against local data.	High levels of accuracy probably required.	

sufficiently accurate, and that local operating practices are adequately reflected. However the process of *establishing* any of the three model types as *operational tools* will require similar processes—e.g. demos, site visits, early model runs.

The similarity scores in Tables 2 to 6 indicate many strong similarities between the three levels of model from a modelling point of view. For seven of the dimensions (classed as ***) there are no clear differences between any of the three model types. For a further sixteen dimensions (classified as **) two of the model levels have no clear differences. However for each of these 16 one of the model levels (split approximately equally between levels 3A, 3B and 4) has important differences from the other two. For

Table 6 Key factors in generic and specific models—implementation

Issue	Level 3A: generic model—central	Level 3B: generic model—multiple applicability	Level 4: Specific model	Similarity
Capability to use it	May not be handed over.	May not be handed over.	May not be handed over.	***
	If handed over, ideally low required user capability, clean and transparent input/output interfaces. If user was involved in development, may be less need for this.	If handed over, ideally low required user capability, clean and transparent input/output interfaces.	If handed over, ideally low required user capability, clean and transparent input/output interfaces. If user was involved in development, may be less need for this.	
Establishing model as operational tool	Demo and workshops of validated model with key stakeholders. Use on currently important issues/scenarios. Demonstration that model works on "real" important issues.	Depending on model, local site visits, demo/workshops, validation and supported model runs may be required. Use on currently important issues/scenarios. Demonstration that model works on "real" important issues.	Demo and workshops of validated model with key stakeholders. Use on currently important issues/scenarios. Demonstration that model works on "real" important issues.	***
Post development user support or use of model	If not handed over, modelling team must be geared up to quickly perform runs and communicate results effectively.	If not handed over, modelling team must be geared up to quickly perform runs and communicate results effectively. This may be "remote" support.	If not handed over, modelling team must be geared up to quickly perform runs and communicate results effectively.	***
	If handed over, geared towards handover to user(s) at the particular department. If the users are technically proficient or involved in model development, less need for "clean" user interfaces, documentation etc.	If "handed over", geared towards multiple (geographically spread) users and/or regional/national teams with clean user interface and user guide/documentation.	If handed over, geared towards particular central user(s). If the users are technically proficient or involved in model development, less need for "clean" user interfaces, documentation etc.	
Desire to use it	Should be high, as model was commissioned, but central politics still a factor.	Depends on perception of quality, coverage, plus existence of other models and local politics.	Should be high, as model was locally commissioned, local politics still a factor.	**
	Depends on perception of quality, coverage, plus existence of other models		Depends on perception of quality, coverage, plus existence of other models	
Hardware/software requirements	Ideally inexpensive or free, but some investment in software may be needed.	Probably more important that no investment in software is required.	Ideally inexpensive or free, but some investment in software may be needed	**

only one dimension, ‘target level of use’, (classified *) is there a clear difference between all three model levels.

7 Conclusions

The conclusions present a summary of the findings against the two major objectives.

7.1 To compare the characteristics of ‘generic’ and ‘specific’ models and their success or otherwise in modelling the flow of emergency patients in acute hospitals

Using evidence from the literature, an informal survey, and personal experience, a simple initial framework of four levels ranging from specific models to generic principles, was proposed. It is summarised in Fig. 1 and is based on the key dimensions of transportability and abstraction.

Further analysis then suggested a much richer picture and Tables 2 to 6 provide a systematic comparison of level 3 (divided into 3A and 3B) and level 4 models, in terms of 24 dimensions organised under five main headings: project initiation, design and build, data, validation and implementation. There is much common ground between the model types, but also some crucial distinctions for the model builder.

Further work could be possible to compare these findings generated from a health setting to findings from other settings, such as military based models.

7.2 To learn lessons on the design, validation and implementation of these models with a view to the future development of a ‘generic’ hospital model for emergency patients

There is much evidence of models, especially simulation models developed in the main areas of acute hospitals that deal with emergencies—A&E, inpatient beds, surgery, Intensive Care and diagnostics.

A&E models usually focus on time of day and day of week demand issues, staff scheduling, changing working practices, physical constraints such as cubicles and whole system issues such as diagnostics and bed management. KPIs 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, and often by specialty. Elective and emergency patients must be modelled. Key resources are typically beds (staffing is usually not modelled). TOD issues are usually excluded. Key factors are average/variability of LOS by DOW. KPIs are typically occupancy and ‘service failures’, e.g. surgery cancellations and/or ‘trolley waits’ in A&E.

Surgery models tend to concentrate on bed requirements pre and post surgery, plus preparation and turnaround issues, staffing requirements, surgery time and post op recovery. Emergency and elective patients both use theatres. Theatre scheduling algorithms are sometimes attempted. Time of day and day of week are key factors. KPIs are usually patient throughput and utilization of beds, theatres and staff.

Intensive Care models usually focus on beds and specialist nurses. Time of day and day of week are important for demand and staffing requirements. Demand is from emergency and elective surgery, A&E, wards and other hospitals. There are often problems with moving patients to lower dependency beds where appropriate. Costs of specialist beds and nurses are key. KPIs are utilization of beds and nurses, patient throughput and risks of non admission of patients.

Diagnostic models are of two types, clinical laboratory models (e.g. blood tests) and radiology models (i.e. X Rays). Both have similar features—time of day/day of week demands, staff to test skill mixes, equipment availability. Demand is from wards, outpatients, community and A&E. Common issues are multitasking, working practices and test batching. KPIs include patient waiting time and throughput and utlilization of staff and equipment.

Across all the above models there are similar features of design, data, validation and implementation. Design is typically through discussion with local experts, although bed management models appear to be more intuitively designed with less involvement of local expertise. 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 comparison against historical data and discussion with local experts. Implementation is surprisingly rare. There are usually 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, requiring a change in working practices or funding. There is no clear difference between generic and specific models in implementation rates. Some papers provided an analysis of the key success factors in getting models implemented, but there was surprisingly little consensus on the key factors beyond ensuring client involvement. This lack of agreement on key success factors may provide some clues as to the variability in observed implementation rates.

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

There are a few examples of attempts to model whole hospitals. However the published literature focuses on what we have described as flexible 'generic frameworks' rather than generic whole hospital models.

When considering connectivity between single department models, TOD and DOW considerations will be important, and the following relationships will be important:

- A&E departments often include the effects of bed management in the 'wait for bed' process, and the impact of diagnostics in patient waits for X Ray/blood test results. However, this is usually modelled as the impact of these processes (i.e as unconstrained time distributions), rather than capacity constrained submodels of those processes.
- Bed management models usually model the following sources of admission: A&E, direct emergency admissions and elective patients pre and post surgery
- Surgery models usually have demand inputs from inpatient and daycase beds, ICU, A&E and direct emergency admissions.
- Flows into ICU are from elective/emergency surgery, A&E, direct emergency admissions and wards. The ICU typically discharges patients into lower intensity inpatient beds.
- Finally, diagnostics models usually have demand inputs from inpatient beds, outpatients, A&E and community sources (e.g. GPs). Immediate discharge is assumed.

8 Further work

As noted in the introduction, this paper is part of an ongoing project to investigate the potential in extending the idea of a 'generic' model to a whole hospital. As a next stage the authors intend to develop a (type 3A) generic model of flows of emergency patients through all key departments in acute hospitals. The hope is that the model will be used to identify the general issues faced by acute hospitals in managing the flow of emergency patients, whilst also accounting for the needs of elective and other patients

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References

1. Fletcher A, Halsall D, Huxham S & Worthington D (2007) The DH Accident and Emergency Department model—a national generic model used locally. J Oper Res Soc
2. Gunal M (2008) Simulation modelling for performance measurement in healthcare. PhD Thesis University of Lancaster
3. Jun J, Jacobson S, Swisher J (1999) "Application of discrete-event simulation in health care clinics: A survey" *J*. Oper Res Soc 50:109–123
4. Lowery JC (1998) Getting started in simulation in health care. Proc 1998 Winter Simul Conf
5. Sinreich D, Marmor Y (2004) A simple and intuitive simulation tool for analyzing emergency department operations. Proc 2004 Winter Simul Conf
6. Robinson S, Nance R, Paul R, Pidd M, Taylor S (2004) Simulation model reuse: definitions, benefits and obstacles. Simul Model Pract Theory
7. Steele M, Mollaghasemi M, Rabadi G, Cates G (2002) Generic simulation models of reusable launch vehicles. Proc 2002 Winter Simul Conf
8. Pidd M (1999) Tools for thinking: modelling in management science. Wiley
9. Garcia M, Centeno M, Rivera C, DeCario N (1995) Reducing time in an emergency room via a fast track. Proc 1995 Winter Simul Conf
10. Blake J, Carter M (1996) An analysis of emergency room wait time issues via computer simulation. INFOR 34:263–272
11. Kraitsik M and Bossmeyer (1993) Simulation applied to planning an emergency department expansion. 1993 SCS Western MultiConf Simul: Simul in the Health Scis Services 19–27
12. Kirtland et al. (1995) Simulating an emergency department is as much fun as… Proc 1995 Winter Simul Conf
13. McGuire F (1994) Using simulation to reduce length of stay in emergency departments. Proc 1994 Winter Simul Conf 861–867
14. Ritondo M, Freedman R (1993) The effects of procedure scheduling on emergency room throughput: A simulation study. 1993 SCS Western MultiConf Simul: Simul Health Scis Services 8–11
15. Draeger M (1992) "An emergency department simulation model used to evaluate alternative nurse staffing and patient population scenarios" *Proc.1992 Winter Simul Conf.*
16. Evans G (1996) A simulation model for evaluating personnel schedules in a hospital emergency department. Proc 1996 Winter Simul Conf 1205–1209
17. Kumar A, Kapur R (1989) Discrete simulation application—scheduling staff for the emergency room. Proc 1989 Winter Simul Conf 1112–1120
18. Badri M, Hollingsworth J (1993) A simulation model for scheduling in the emergency room. Int J Opns Prod Mgmt 13:13–24
19. Bodtker K, Wilson L, Godolphin W (1992) Simulation as an aid to clinical chemistry laboratory planning. Proc 1992 Conf. Simul Health Care Social Scis 15–18
20. Godolphin W, Bodtker K, Wilson L (1992) Simulation model.: A tool to help predict the impact of automation in clinical laboratories. Lab Robot Autom 4:249–255
21. Liyange L, Gale M (1995) Quality improvement for the Campbelltown hospital emergency service. 1995 IEEE Int Conf Systems, Man Cyber 1997–2002
22. Horton S (2004) Increasing capacity while improving the bottom line. Frontiers Health Service Manag 20:4
23. Carter M and Lapierre S (2001) Scheduling emergency room physicians. Health Care Manag Sci 4(4), Dec 2001
24. Miller M, Ferrin D, Messer M (2004) Fixing the emergency department: A transformational journey with EDSIM. Proc 2004 Winter Simul Conf 1988–1993
25. Centeno M, Giachetti R, Linn R (2003) A simulation-ILP based tool for scheduling ER staff. Proc 2003 Winter Simul Conf 1930–1938

26. Takakuwa S, Shiozaki H (2004) Functional analysis for operating emergency department of a general hospital. Proc 2004 Winter Simul Conf 2003–2011
27. Blasak R, Armel W, Starks D, Hayduk M (2003) The use of simulation to evaluate hospital Operations between the emergency department and a medical telemetry unit. Proc 2003 Winter Simul Conf 1887–1893
28. Rossetti M, Trzcinski G, Syverud S (1999) Emergency department simulation and determination of optimal attending physician staffing schedules. Proc 1999 Winter Simul Conf 1532–1540
29. Baesler F, DaCosta M, Jahnsen H (2003) The use of simulation and design of experiments for estimating maximum capacity in an emergency room. Proc 2003 Winter Simul Conf 1903–1906
30. Miller M, Ferrin D, Szymanski J (2003) Simulating six sigma improvement ideas for a hospital emergency department. Proc 2003 Winter Simul Conf 1926–1929
31. Wiinamaki A, Dronzek R (2003) Using simulation in the architectural concept phase of an emergency department design. Proc 2003 Winter Simul Conf
32. Blake J, Carter M (1996) An analysis of Emergency Room wait time issues via computer simulation. INFOR 34(4), Nov 1996
33. Badri M, Hollingsworth J (1993) A Simulation model for scheduling in the emergency room. IJOPM 13(3):13–24
34. Lane D, Monefeldt C, Rosenhead J (2000) Looking in the wrong place for healthcare improvements: A system dynamics study of an accident and emergency department. J Oper Res Soc 51:518–531
35. Komashie A, Mousavi A (2005) Modelling emergency departments using discrete event simulation techniques. Proc 2005 Winter Simul Conf 2681–2685
36. Samanha S, Armel W, Starks D (2003) The use of simulation to reduce the length of stay in an emergency department. Proc 2003 Winter Simul Conf 1907–1911
37. Mahapatra S, Koelling C, Patvivatsiri L, Fraticelli B, Eitel D, Grove L (2003) Pairing emergency severity index5-level triage data with computer aided design to improve emergency department access and throughput. Proc 2003 Winter Simul Conf 1917–1925
38. Gonzalez B, Perez P (1994) Evaluation of alternative functional designs in an emergency department by means of simulation. Simul 63(1):20–28
39. Butler T, Reeves G, Karwan K, Sweigart J (1992) Assessing the impact of patient care policies using simulation analysis. J Soc Health Sys 3:38–53
40. Hancock W, Magerlein D, Storer R, Martin J (1978) Parameters affecting hospital occupancy and implications for faculty sizing. Health Services Res 13:276–289
41. Wright M (1987) The application of a surgical bed simulation *model*. Eur J Opl Res 32:26–32
42. Gabaeff S, Lennon J (1991) New computerized technology for the design and planning of emergency departments. Proc Am Hosp Assoc 1–15
43. Vassilacopoulos G (1985) A simulation model for bed allocation to hospital inpatient departments. Simul 45:233–241
44. Altinel I, Ulas E (1996) Simulation modelling for emergency bed requirement planning. Annals of Opns Res 67:183–210
45. Freedman R (1994) Reduction of average length of stay in the emergency room using discrete event simulation. Proc Simul Health Scis 6–8
46. Lennon J (1992) Simulation in the design and planning of emergency departments. 1992 SCS Western MultiConf: Simul Educ Bus, Manag MIS 93–97
47. Williams S (1983) How many intensive care beds are the worst? Crit Care Med 11:412–416
48. Adan I, Vissers J (2002) Patient mix optimization in hospital admission planning: a case study. Int J Oper Production Manag 22(4), 2002
49. Bagust A, Place M, Posnett J (1999) Dynamics of bed use in accommodating emergency admissions: stochastic simulation model. BMJ 319:155–158
50. Nguyen J, Six P, Antonioli D, Glemain P, Potel G, Lombrail G, Le Beux P (2005) A simple method to optimize hospital beds capacity. Int J Medical Informatics 74:39–49
51. Gorunescu F, McClean S, Millard P (2002) A queuing model for bed-occupancy managment and planning of hospitals. J Oper Res Soc 53:19–24
52. Mackay M (2001) Practical experience with bed occupancy management and planning systems: an Australian view. Health Care Manag Sci 4:47–56
53. Harrison G (2001) Implications of mixed exponential occupancy distributions and patient flow models for health care planning. Health Care Manag Sci 4:37–45
54. Harper P, Shahani A (2000) A decision support simulation model for planning and managing hospital bed capacities. Proc Int Conf Health Scis Simul 2000
55. Harris R (1985) Hospital bed requirements planning. Eur J Oper Res 25:121–126
56. Dumas B (1984) Simulation model for hospital bed planning. Simul 69–78, August 1984
57. Vissers J (1998) Patient flow-based allocation of inpatient resources: A case study. Eur J Oper Res 105:356–370
58. Currie K, Iskander W, Michael L, Coberley C (1984) Simulation modelling in health care facilities. Proc 1984 Winter Simul Conf 713–717
59. Kwak N, Kutzdrall P, Schmitz H (1975) Simulating the use of space in a hospital surgical suite. Simul 24:147–152
60. Kutzdrall P, Kwak N, Schmitz H (1981) Simulating space requirements and scheduling policies in a hospital surgical suite. Simul 27:163–171
61. Olson E, Dux L (1994) Computer model targets best route for expanding hospital surgicenter. Indust Engng 26:24–26
62. Murphy D, Sigal E (1985) Evaluating surgical block scheduling using computer simulation. Proc 1985 Winter Simul Conf 551–557
63. Fitzpatrick K, Baker J, Dave D (1993) An application of computer simulation to improve scheduling of hospital operating room facilities in the United States. Int J Comp Applic Technol 6:215–224
64. Longo M, Masella C (2002) Organisation of operating theatres: an Italian benchmarking study. Int J OperProd Manag 22 (4):425–444
65. Lovejoy W, Li Y (2002) Hospital operating room capacity expansion. Manag Sci 48(11):1369–1387
66. Blake J, Carter M, O'Brien-Pallas L, McGillis-Hall L (1995) A surgical process management tool. Medinfo Pt 1:527–531
67. Lowery J, Davis J (1999) Determination of operating room requirements using simulation. Proc 1999 Winter Simul Conf 1568–1572
68. Centeno M, Albacete C, Terzano D, Carrillo M, Orgazon T (2000*)* A Simulation study of the radiology department at JMH. Proc 2000 Winter Simul Conf 1978–1984
69. Ramis F, Palma J, Baesler F (2001) The use of simulation for process improvement at an ambulatory surgery center. Proc 2001 Winter Simul Conf 1401–1404
70. Kwak N, Kuzdrall P, Schmitz H (1976) The GPSS simulation of scheduling policies for surgical patients. Manag Sci 22(9), May 1976
71. Bowers J, Mould G (2002) Concentration and the variability of orthopaedic demand. J Oper Res Soc 53:203–210
72. Lowery J (1992) Simulation of a hospitals surgical suite and critical care area. Proc 1992 Winter Simul Conf 1071–1078
73. Lowery J (1993) Multi-hospital validation of critical care simulation model. Proc 1993 Winter Simul Conf

74. Lowery J, Martin J (1992) Design and validation of a critical care simulation model. J Soc Health Syst 3:15–36
75. Zilm F, Arch D, Hollis R (1983) An application of simulation modelling to surgical intensive care bed need analysis in a university hospital. Hospital Health Services Admin 28:82–101
76. Romain-Jacur G, Facchin P (1987) Optimal planning of a pediatric semi-intensive care unit via simulation. Eur J Opl Res 29:192–198
77. UK Department of Health (1999) Comprehensive critical care. A review of adult critical care services. www.doh.gov.uk/nhsexec/compcritcare.htm
78. Plati C, Lemonidou C, Priami M, Baltopoulos G, Mantas J (1996) The intensive care units in greater Athens: needs and resources. Intensive Crit Care Nurs 12:340–345
79. Kapadia A, Chan W, Sachdeva R, Moye L, Jefferson L (2000) Predicting duration of stay in a pediatric intensive care unit: a Markovian approach. Eur J Oper Res 124:353–359
80. Southgate H (1999) Critical analysis of access to and availability of intensive care. Intensive Crit Care Nurs 15:204–209
81. Pirret A (2002) Utilizing TISS to differentiate between intensive care and high dependency patients and to identify nursing skill requirements. Intensive Crit Care Nurs 18:19–26
82. Williams S, Coombs M, Lattimer V (2003) Workforce planning for critical care: a rapid review of the literature (1990–2003). Kings Fund
83. Costa A, Ridley S, Shahani A, Harper P, De Senna V, Nielsen M (2003) Mathematical modelling and simulation for planning critical care capacity. Anaesthesia 58:320–327
84. Demirel T, Onut S, Erdem H (1999) A simulation based planning approach to a hospital system design. Summer Comp Simul Conf, Soc for Comp Simul Int
85. Ridley S, Jones S, Shahani A, Brampton W, Nielsen M, Rowan K (1998) Classification trees. a possible method for iso-resource grouping in intensive care. Anaesthesia 53:833–840
86. Griffiths J, Price-Lloyd N, Smithies M, Williams J (2005) Modelling the requirement for supplementary nurses in an Intensive Care unit. J Oper Res Soc 56:126–133
87. Cahill W, Render M (1999) Dynamic simulation modelling of ICU bed availability. Proc 1999 Winter Simul Conf 1573–1576
88. Bonvissuto C (1994) Avoiding unnecessary critical care costs. Healthc Financial Manag 48(11):47–50
89. Ridge J, Jones S, Nielsen M, Shahani A (1998) Capacity planning for intensive care units. Eur J Oper Res 105:346–355
90. Kim S, Horowitz I, Young K, Buckley T (1999) Analysis of capacity management of the intensive care unit in a hospital. Eur J Oper Res 115:36–46
91. Shmueli A, Sprung C, Kaplan E (2003) Optimizing admissions to an intensive care unit. Health Care Manag Sci 6:131–136
92. O'Kane P (1981) A simulation model of a diagnostic radiology department. Eur J Oper Res 6:38–45
93. Klafehn K (1987) Impact points in patient flows through a radiology department provided through simulation. Proc 1987 Winter Simul Conf 914–918
94. Coffin M, Lassiter G, Killingsworth B, Kleckley J (1993) A simulation model of an X Ray facility. 1993 SCS Western multiConf on Simul: Simul Health Scis Services 914–918
95. Ramis F, Palma J, Estrada V, Coscolla G (2002) A Simulator to improve patients service in a network of clinic laboratories. Proc 2002 Winter Simul Conf 1444–1447
96. Berchtold G, Blaschke H, Hanssmann F, Liebl F, Braun S, Vogt W, Eckert M, Hoffmann G, Klose S (1994) Simulation modelling as a tool to evaluate alternative configurations of clinical laboratories. Simul 63(2):108–120
97. Couchman A, Jones D, Griffiths K (2002) Predicting the future performance of a clinical biochemistry laboratory by simulation. Simul Model Pract Theory 10:473–495
98. Ramakrishnan S, Nagarker K, DeGennaro M, Srihari K, Courtney A, Emick F (2004) A study of the CT Scan area of a healthcare provider. Proc 2004 Winter Simul Conf 2025–2031
99. Van Merode G, Hasman A, Derks J, Goldschmidt SB, Schoenmaker B, Oosten M (1995) Decision support for clinical laboratory capacity planning. Int J Bio-Med Comput 38:75–87
100. Hancock W, Walter P (1979) The use of computer simulation to develop hospital systems. Simuletter 10:28–32
101. Swisher J, Jun J, Jacobson S, Balci O (1997) Simulation of the Queston physician network. Proc 1997 Winter Simul Conf 1146–1154
102. Moreno L, Aguilar R, Martin C, Pineiro J, Estevez J, Sigut J, Sanchez J, Jimenez V (1999) Patient centred simulation tool for aiding in hospital management. Simul Pract Theory 7:373–393
103. Pitt M (1997) A generalised simulation system to support strategic resource planning in healthcare. Proc. 1997 Winter Simul Conf 1155–1162
104. Dittus R, Klein R, DeBrota D, Dame M, Fitzgerald J (1996) Medical resident work schedules: design and evaluation by simulation model. Manag Sci 42(6), Jun 1996
105. Harper P (2002) A framework for operational modelling of hospital resources. Health Manag Sci 5(3), Aug 2002