Session 6
Simulation in Health

DEVELOPING SIMULATION MODELS OF POSSIBLE FUTURE SCENARIOS FOR THE DELIVERY OF ACUTE CARE IN NHS AYRSHIRE AND ARRAN TO INFORM THE DECISION MAKING PROCESS

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ABSTRACT

This paper describes the simulation study carried out in NHS Ayrshire and Arran as part of the Review of Services Project. The project explores the development of new proposals for a major reconfiguration of services.

The main objectives were to look at volumes of patients attending the A&E departments and flowing through the inpatient sites under the different proposed models of care, and then to assess bed capacity requirements for all specialties under different scenarios. Using the lessons learnt from previously presented proposals, computer simulation models were built in Simul8 for each of the proposed scenarios for the future delivery of care. The paper is about the creation of those models, the assumptions made and the interpretation of the outputs generated. The paper reflects the difficulties in giving a recommended number of beds and the approach accepted for this study.

Keywords: Healthcare Reorganisation, Simulation Modelling, Bed Planning

1. INTRODUCTION

NHS Ayrshire & Arran is currently reviewing the provision of emergency and unscheduled care, elective and rehabilitation services. As part of this review, simulation models have been developed to aid decision making on the delivery of a range of services. The reason for this was that the team tasked with developing these proposals wished to use simulation models with the aim of determining necessary bed capacity. Models have been constructed using interviews with key clinical staff, activity data and patient records to establish referrals, rates and lengths of stay. Despite questions about the relevance of the data to the proposed new system of service delivery, a series of recommendations have been made. Sensitivity analysis has been carried out and reported, as well as a series of verification and validation checks on the results.

A recent review of the legacies of simulation modelling in healthcare, Eldabi at al (2007), argues that applications for operational decision support have become increasingly significant and describes Simulation modelling as an ideal method of evaluating strategies that authorities may have in mind. Our paper aims to demonstrate the usefulness of applying simulation for re-organization of healthcare services and provides a case study on bed planning for a set of proposals.

The paper is divided into 10 sections. The first two sections introduce the background of the study. Section three describes patient flows in the development of the conceptual model followed by an overview of the computer model in section 4. Sections five and six explain simulation scenarios, the data used and assumptions made in this study. Section seven reports on the analysis of the outputs from the modelling and makes recommendations on the number of beds required under these proposals. Section eight describes how this modelling was validated and verified and finally sections nine and ten present some discussion points and give a brief conclusion.

2. BACKGROUND TO THE STUDY

Ayrshire is situated in south-west Scotland on the Firth of Clyde coastline. Consisting of the local authorities of North, East and South Ayrshire, the area stretches from Largs in the north to Ballantrae in the south and from the west coast to Muirkirk and Cumnock in the east, and includes the islands of Arran and Cumbrae.
NHS Ayrshire & Arran provides a comprehensive range of health services and healthcare to a population of around 367,000. There are two district general hospitals in the health board area, Ayr Hospital and Crosshouse Hospital.

2.1 REVIEW OF SERVICES (ROS)

This is the second time that proposals for the future delivery of care in Ayrshire & Arran have been developed, due to a ministerial decision, following the Scottish elections 2007, to overturn the health board's previous plans to reorganise services including the downgrading of Ayr Hospital A&E. Simulation modelling was carried out to inform the decision making for the first set of proposals, Dickson and Lara (2007). For this new set of proposals, the Cabinet Secretary set constraints to maintain A&E services at Ayr Hospital and retain as many of the original proposals as possible. The RoS team was tasked with developing new proposals that Simulation would inform in terms of volumes of patients going through the system and bed capacity requirements at specialty level.

3. CONCEPTUAL MODELLING

The first stage in a simulation study is to develop a conceptual model of the system to be analysed. As described in a recent study by Balci and Ormsby (2007): "A simulation conceptual model represents the highest layer of abstraction that is closer to the level of thinking of managers, analysts, and simulation model designers".

The main conceptual model was developed consulting the RoS team and other healthcare professionals. In addition, the experience and lessons learnt from the models built in the first set of proposals for the RoS project were incorporated. The objective was to formulate a generic conceptual model with two complete Emergency Care Facilities (ECF) and from which other scenarios with proposals would be developed in line with the emerging shortlist of options for the future delivery of acute care.

The patient pathways through the models start with arrival at the A&E departments from a specific source of referral such as emergency services, GP referrals or self presenting patients. As soon as they arrive in the system children are transferred to the Paediatrics facility, which is on the Crosshouse Hospital site. Regardless of their means of entering the system e.g. by ambulance, self presentation etc. all patients are assigned a triage category, determined by initial assessment from medical or nursing staff in the A&E department. The five triage categories and descriptions are shown in Table 1 below.

Number	Colour	Definition	Description
1	Red	Immediate resuscitation	Patients in need of immediate treatment for preservation of life
2	Orange	Very urgent	Seriously ill or injured patients whose lives are not in immediate danger
3	Yellow	Urgent	Patients with serious problems, but apparently stable condition
4	Green	Standard	Standard A&E cases without immediate danger or distress
5	Blue	Non-urgent	Patients whose conditions are not true accidents or emergencies

Table 1: Manchester Triage Scale:

Depending on the triage category, patients are routed into the appropriate area within the A&E department or to an Assessment Unit, (this would be a new facility that would alter the flow of patients through the department and reduce the number of patients with inappropriate admissions to an inpatient bed). If patients are in the lower spectrum of triage (categories blue or green) and there is a closer Community Casualty Facility (CCF) patients are routed to attend there instead of the A&E.

After emergency treatment patients are either discharged or become inpatients under the relevant speciality. The second stream of patients entering the system is the scheduled arrivals to the inpatient sites for elective care procedures. The third entry point to the system can be from direct GP admissions where patients enter the system directly to an inpatient bed. An overview of the entire conceptual model is shown in Figure 1.

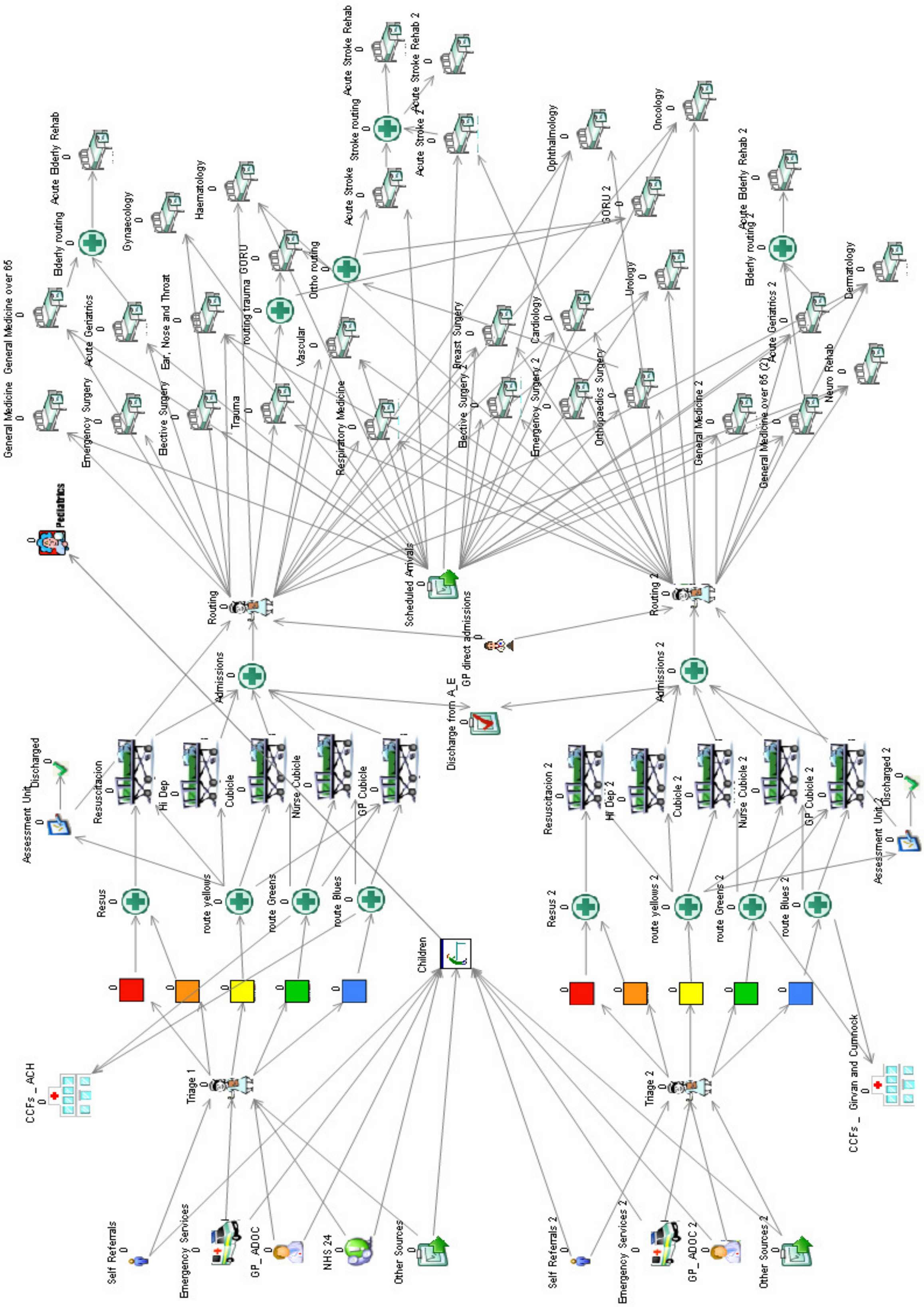

Figure 1: Conceptual simulation model

The conceptual model was built based on having two full ECFs (scenario 7) and from this, new scenarios were created as variations on the level of service provision at Ayr Hospital. The flow of patients was altered depending on the model.

Once patients are admitted to a bed in the appropriate facility they stay for a length of time based on historical data and the assumed impact of changes in service delivery.

4. THE COMPUTER MODEL

The computer model in Simul8 was built using the conceptual model developed to understand the system configuration and the knowledge of the processes happening in that system. Statistical analysis of historical data was used to inform the model.

The model development and configuration focused on delivering the outputs that would influence the decision making process. Determining the bed capacity requirements was considered to be the main objective. The models were therefore built, focusing on determining occupancy, by assessing issues and processes within the flow of patients.

The attributes of the patients are coded within the model in the form of labels including: age; type of care required (emergency or elective, surgical or medical), triage category, length of stay, speciality and whether the patient was admitted or not.

Depending on their attributes, patients flow through the model. These flows are configured using proportions of past presentations. This means that the model is incredibly data-driven. As is often the case with data, the historical data collected was not in the correct form to input in the model and it was very difficult and time consuming to identify patients and their categorization under specialties. The length of time patients' stay was configured according to distributions created using historical data and input into the model in the form of probability profiles. Literature and practice would suggest that using a distribution is a more accurate way to assess bed capacity as it better reflects the randomness of the real world.

The models simulate a period of two years and the time unit is in hours. A warm-up period is used so that the model does not start when the hospital is empty. A graphical method was preferred for estimating the warm-up period due to its simplicity; it involves visual inspection of the time-series output and human judgement. Robinson and Ioannou ranked this method the best however it has disadvantages and relies upon a subjective assessment and is probably affected by the experience of the analyst. The warm-up period was estimated to be six weeks by inspecting time-series of key output statistics such as occupancy levels of specialties.

5. SIMULATION SCENARIOS

Six possible scenarios were developed with the main variation represented in the configuration of the front door at the Ayr Hospital site. The different scenarios follow the description of the options. In addition, the models differ in the configuration of sub-specialty care behind the front door. Below the different scenarios are listed and briefly described by the main clinical characteristics that led modelling.

Scenario 7 has two ECFs led by an A&E consultant all of the time at Crosshouse and Ayr Hospital treating all patients coming from any source of referral.

Scenario 6 has the ECF at Ayr Hospital led by A&E consultants during peak hours with medical and surgical receiving.

Scenario 5 has an ECF at Ayr Hospital led by consultants. There is no Surgery department in Ayr hospital. So, non-self presenting patients would bypass Ayr Hospital and go straight to the Assessment Unit at Crosshouse. Self-presenting patients would be stabilised and treated and then transferred to the most appropriate facility.

Scenario 4 is the status quo scenario, the existing service model of care. It had previously been modelled in an earlier stage of the project.

Scenario 3 has an Acute Physician in the ECF, a Combined Assessment Unit and a surgical department at Ayr Hospital.

Scenario 2 has ECF led by Acute Physician during peak hours (10am to 10pm) supported by an Emergency Care Practitioner (ECP) at Ayr Hospital. There would be a medical assessment unit but no emergency surgical service in this model.

Scenario 1 has an ECF led by ECP/GP and there is no surgical department in Ayr Hospital. Ayr Hospital has no assessment unit but the provision of sub-acute beds for emergency patients with less serious acute medical conditions.

6. DATA AND ASSUMPTIONS

The model makes use of the most up to date validated data available to populate the pathways of care associated with each of the options. Whilst the model makes use of historical data, simulation interprets the patient flows in light of changes to the patient pathway as described in the proposals set out in each of the options.

The data used in the Simulation Modelling process was taken from A&E activity data at Crosshouse and Ayr Hospitals from April 2006 to March 2007 and inpatient activity from the Information Services Division validated SMR01 dataset from April 2006/ March 2007.

As with any model of service redesign a number of assumptions had to be made based on the best available evidence and intelligence. These assumptions are set out below.

Triage Patterns
It was assumed that past presentations at Ayr and Crosshouse A&E are representative of future patterns of demand in terms of volumes of patients and sources of referrals. It has been assumed that current triage proportions by source of referral into A&E would continue and current proportions of admissions to the inpatient sites depending on the triage category would also remain constant.

Community Casualty Facility Catchment
Within the simulation modelling patients have been rerouted to Community Casualty Facilities (CCFs) based on their home postcode sector and their triage category (triage category Blue and Green patients go to their closest CCFs).

Assessment Unit
In terms of the Assessment Unit, it has been assumed that 65% of Yellow patients go through this facility and stay in a bed for 24 hours and, that following this, 40% would be discharged and 60% become inpatients.

Inpatient Activity
It has been assumed that past inpatient activity is representative of future patterns of demand in terms of volumes of emergency and elective inpatients, specialities and lengths of stay.

Community Hospitals Activity
For this study, based on advice from GPs and activity at GP led services at East Ayrshire Community Hospital and Davidson Hospital, it has been assumed that sub-acute beds for model 1 would have a maximum length of stay of 2 weeks and 70% of patients would be discharged within 3 days.

GP Referrals
Based on past behaviour, it is assumed that there would be approximately 2000 GP direct referrals per annum to the inpatient services.

Specialty Activity Data
Patients were classified under specialties for the simulation modelling based on the data records and a set of assumptions to identify patients by diagnoses or procedures codes in the specialties under the proposals.

Bypasses or Transfers
Due to different configurations of the front-door services at Ayr Hospital, it has been assumed that different numbers of patients would bypass or transfer from Ayr Hospital to Crosshouse Hospital. Individual assumptions have therefore been made for each of the options modelled, based on how the front-door services operate, the needs of patients, as determined by triage category, whether they require surgical or medical care and the time of the day they present at the A&E department. The assumptions used are as follows:

-Model 1 rerouted all non-self-presenting Red, Orange and 50% of Yellow triaged patients to Crosshouse Hospital.

-Model 2 rerouted all non-self-presenting Red and Orange triage patients to Crosshouse. Patients triaged as yellow surgical patients are also re-routed or transfer to the Assessment Unit at Crosshouse Hospital.

-Model 3 all non-self-presenting Red and Orange triaged patients are re-routed to Crosshouse, plus Yellow triaged medical patients during the night.

-Model 5 rerouted non-self-presenting surgical patients to Crosshouse, with self-presenting surgical patients being transferred from Ayr Hospital to the Assessment Unit at Crosshouse Hospital.

7. ANALYSIS OF OUTPUTS

The results are of trials of 15 runs, being the most appropriate number of replications after testing outputs with diverse numbers of runs. As a result, 95% confidence intervals were generated for items entered in each of the facilities of interest and for the average and maximum queue size for each of the specialties for each of the scenarios developed. Volumes of patients for each of the triage categories under each scenario were given as well as volumes of patients attending each of the CCFs.

We explored the time graphs for each of the specialties, which represent the occupancy across two years, for instance we can see the occupancy of General Medicine beds in the time graph in Figure 2.

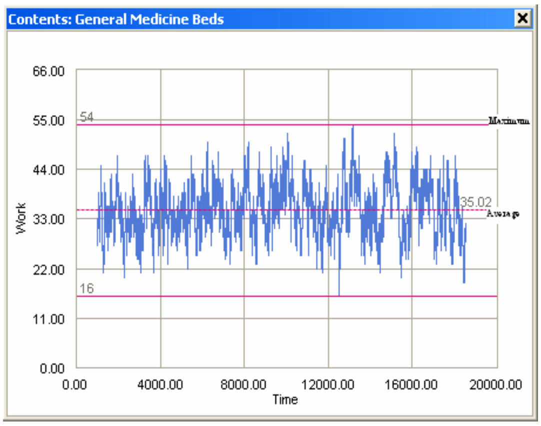

Figure 2: Time graph of the contents of the General Medicine beds

7.1 RECOMMENDED NUMBER OF BEDS

The average number that the model output suggests would not cope with the demand for services all the time. The maximum number of beds may only be reached on a limited number of occasions during a year. Due to an accepted degree of flexibility between specialties and bearing in mind that it is highly unlikely that all specialties would need their maximum number of beds at the same time it was considered inappropriate to use the maximum occupancy figure in planning bed capacity because it would overestimate bed requirements. Therefore, neither has been used in isolation to determine a recommended number of beds for each specialty or for a model.

An approach was used to calculate bed numbers that accounts for both average and maximum occupancy. Using the average as baseline for the recommended number of beds and taking into account the maximum requirement proposed by the models, the formula adds to the average half of the variation between the average and the maximum which results in the formula below and can be used to identify an appropriate number of beds for each specialty.

$$\textit{Formula} = \textit{Average} + (\textit{Maximum} - \textit{Average})/2 = (\textit{Average} + \textit{Maximum})/2$$

Accordingly, the predicted numbers of beds required for each of the specialties were provided for each of the models. These were re-arranged according to the preferred hospital under the proposals at that particular moment in time and so total number of beds per hospital was given for each of the models that represent a different model of care. This can be seen in Table 2.

7.2 SENSITIVITY ANALYSIS

A number of assumptions were made when building the model and the sensitivity of these assumptions was tested to assess the degree of uncertainty around estimations by changing different inputs to the model and assessing the impact this has on the results. For instance, exploring how changes in the percentage of patients discharged from the Assessment Units affects the inpatient activity and the resulting effects on capacity requirements. Specifically, the percentage of patients discharged from the Assessment Units was increased to 60% and reduced to 20% and 0%. The impact on the total bed number was limited. This amounted to be between 55 and 60 beds per 20% variation in the discharge rate.

The sensitivity of the number of attendances at A&E was tested with an increase of 10% of all attendances across the two hospitals for the scenario represented in model 7. The higher volumes reflected around 2800 more unscheduled admissions per year and an augment of 47 in the total number of beds required.

The sensitivity analysis explored the impact of a reduction of self-presentations at Ayr Hospital with increasing self-referrals at Crosshouse. This was undertaken to test the possibility that the local population might favour Crosshouse as it could be seen as the specialist centre with full range of specialist care.

To assess the impact of such a change on the capacity requirements of each model the number of self-presentations at Ayr Hospital was reduced by 10% with a corresponding increase at Crosshouse. This resulted in approximately 2000 additional patients attending A&E at Crosshouse Hospital. These patients represented a proportionate cross-section of triage category and had a minimal impact on the required number of Assessment Unit beds and inpatient beds.

	Model 7			Model 6			Model 5			Model 3			Model 2			Model 1		
Crosshouse Hospital	*Ave*	*Max*	*Prop*	*Ave*	*Max*	*Prop*	*Ave*	*Max*	*Prop*	*Ave*	*Max*	*Prop*	*Ave*	*Max*	*Prop*	*Ave*	*Max*	*Prop*
Emergency Surgery	27	46	**37**	29	49	**40**	41	63	**52**	29	49	**40**	41	65	**53**	38	59	**49**
Vascular Surgery				15	29	**22**	15	29	**22**	15	28	**22**	15	28	**22**	14	27	**21**
Cardiology	8	15	**12**	17	34	**26**	17	34	**26**	17	33	**25**	17	33	**25**	15	30	**23**
ENT	6	17	**12**	6	17	**12**	6	17	**12**	6	17	**12**	6	17	**12**	6	17	**12**
Elective Surgery	19	34	**27**	19	34	**27**	19	34	**27**	19	34	**27**	19	34	**27**	19	34	**27**
Acute Geriatrics	35	54	**45**	35	54	**45**	35	55	**45**	35	54	**45**	35	54	**45**	35	53	**45**
Haematology	3	9	**6**	3	9	**6**	3	9	**6**	3	9	**6**	3	9	**6**	3	9	**6**
Gynaecology	11	23	**17**	11	23	**17**	11	24	**18**	11	24	**18**	11	24	**18**	12	24	**18**
General Medicine	35	57	**47**	35	57	**47**	37	59	**48**	38	60	**50**	39	61	**50**	51	77	**65**
General Medicine over 65	37	58	**48**	37	58	**48**	39	61	**51**	40	63	**52**	41	65	**54**	42	64	**54**
Acute Elderly Rehab	104	134	**120**	104	134	**120**	110	140	**125**	111	141	**127**	114	145	**130**	115	146	**131**
Acute Stroke	6	15	**11**	12	25	**19**	12	25	**19**	12	25	**19**	12	24	**19**	11	24	**18**
Acute Stroke Rehab	18	31	**25**	18	31	**25**	18	31	**25**	18	31	**25**	18	31	**25**	17	29	**23**
Trauma	13	24	**19**	18	35	**27**	18	35	**27**	18	33	**26**	18	34	**27**	17	32	**25**
Orthopaedics	6	15	**10**															
GORU	19	33	**27**	19	33	**27**	19	33	**27**	19	33	**27**	20	33	**27**	19	32	**26**
Respiratory Medicine	64	86	**76**	64	86	**76**	64	86	**76**	64	86	**76**	64	86	**76**	94	126	**110**
Dermatology	7	16	**12**															
Assessment Unit	32	52	**42**	32	52	**42**	38	60	**50**	34	55	**45**	36	57	**47**	37	59	**48**
Total number of beds at Crosshouse	448	720	**593**	473	760	**626**	502	794	**656**	489	776	**642**	508	799	**663**	543	842	**701**
Ayr Hospital																		
Emergency Surgery	13	28	**21**	11	24	**18**				11	24	**18**						
Vascular Surgery	15	29	**23**															
Cardiology	10	20	**15**															
Elective Surgery	10	22	**17**	10	22	**17**	10	22	**17**	10	22	**17**	10	22	**17**	10	22	**17**
General Medicine	22	38	**31**	22	38	**31**	20	36	**29**	19	35	**28**	18	33	**26**			
General Medicine over 65	25	43	**34**	25	43	**34**	23	40	**32**	22	39	**31**	21	38	**30**	15	29	**23**
Acute Geriatrics	26	43	**35**	26	43	**35**	26	42	**35**	26	42	**35**	26	43	**35**	25	41	**33**
Acute Elderly Rehab	73	96	**85**	73	96	**85**	69	91	**81**	66	89	**78**	63	85	**75**	51	70	**61**
Acute Stroke	6	15	**11**															
Acute Stroke Rehab	14	27	**21**	14	27	**21**	13	26	**20**	13	25	**19**	13	25	**20**	12	24	**19**
Breast Surgery	3	11	**8**	3	11	**8**	3	11	**8**	3	11	**8**	3	11	**8**	3	11	**8**
Trauma	6	11	**9**															
Orthopaedics	8	16	**13**	15	28	**22**	15	28	**22**	15	28	**22**	15	28	**22**	15	28	**22**
GORU	14	27	**21**	14	27	**21**	15	27	**21**	15	27	**22**	15	27	**21**	14	26	**21**
Respiratory Medicine	36	48	**42**	36	48	**42**	36	48	**42**	36	48	**42**	36	48	**42**			
Dermatology				7	16	**12**	7	16	**12**	7	16	**12**	7	16	**12**	8	16	**12**
Urology	14	29	**22**	14	29	**22**	14	28	**21**	13	27	**21**	13	27	**21**	12	24	**18**
Ophthalmology	3	10	**7**	3	10	**7**	3	11	**7**	3	10	**7**	3	10	**7**	3	10	**7**
Assessment Unit 2	18	34	**27**	18	34	**27**	16	32	**24**	16	32	**25**	14	30	**22**			
Sub-Acute Beds																55	80	**68**
Total number of beds at Ayr	318	547	**442**	293	496	**402**	271	459	**371**	276	477	**385**	258	443	**358**	223	381	**309**
Total number of beds			**1035**			**1028**			**1027**			**1027**			**1021**			**1010**

Table 2: Average and maximum bed occupancy for each specialty and recommended number of beds for each scenario modelled. Totals for each hospital under each model ** Blank cells mean that the specialty would not be delivered in that Hospital under the specific model*

8. VALIDATION AND VERIFICATION

The A&E activity data came from two hospitals, and there were differences in the activity at the two hospitals for profiles of patients in terms of their gravity and source of referral. This led the RoS team to undertake an audit of the way patients are triaged in each of the hospitals and inconsistencies with the recommended Manchester triage.

The model was run with three variations on the data: (1) with the current triage data from the two sites for each of them, (2) assuming Ayr Hospital would behave as Crosshouse so using Crosshouse A&E data for the two hospitals and (3) using the average of the two current presentations profiles for the two sites. This was done to check the impact of the way that patients are triaged and the subsequent influence on the system in terms of volumes and bed capacity. It also allowed consideration and decision-making around the use of the datasets in the final model.

The outputs of the models have been compared against current performance, for instance the numbers of unscheduled admissions at both sites per year that would happen under each of the models against the number of admissions in one year worth of data. These verified the differences between the front door scenarios and the future effect on the inpatient sites.

Similarly the outputs generated were evaluated against the results from the modelling undertaken in earlier stages of the project and verified the differences due to variation in data and assumptions.

At various stages in the model building process time was taken to consult on the models themselves and the output that they were generating. The RoS team was asked to input to the assumptions used in the model and to comment on the output from the model in light of these assumptions. Using this feedback mechanism has developed a degree of confidence in the findings of the models and their use in the review process.

9. DISCUSSION

The data analysis undertaken for this study raised a number of irregularities in the current way of triaging patients at Crosshouse and Ayr Hospital. The fact that we used current data to run the models does not account for future agreement and equity of triage across the two hospitals. So, once the triage process is standardised new trials of the models will be run with the updated data.

It is assumed that past inpatient activity is representative of future patterns of demand in terms of volumes of emergency and elective inpatients, specialities and lengths of stay. However, currently elective care is affected by unscheduled emergency care and this is an issue that is expected to be resolved with the Review of Services project. Under the proposals, elective care would be better planned and work more independently and would not be affected by emergency activity. Therefore, a better use of the beds is expected with smoother occupancy levels when separating emergency and elective care.

After presenting the time graphs for the occupancy at the specialties, it became apparent that it would be useful to be able to see time graphs of the trials results. These would show confidence intervals represented in a graph with the variation over time. Unfortunately, the software does not provide these graphs and it would be extremely time-consuming to do it.

It is assumed that patients are rerouted to Community Casualty Facilities (CCFs) based on their home postcode sector and their gravity of illness (Blue and Green patients go to their closest CCFs). This analysis has caveats associated with the assumption made that people are at home when they have an accident or become unwell and they attend the closest CCF according to the grouping by postcode sector considered.

Based on the proposals from the RoS Project, the provision of services in the community is likely to have an impact on the number of patients going to the acute sites. Further analysis will be undertaken to account for those patients that would attend the community facilities rather than the District General Hospitals under the new proposals. The model will be re-adjusted to account for this and the additional rehabilitation capacity in the community setting.

It is anticipated that this Simulation study will be used for the Implementation stage of the project, the preferred model could be refined and improved by adding details on the flow of patients, identification of subspecialties and the use of updated data. Nevertheless, as Eldabi et al (2007) argues, “A major challenge lies in persuading service providers and clinicians that simulation, as system level tool, can make a critical contribution”.

10. CONCLUSIONS

The simulation model has been used to demonstrate the required number of beds at Ayr and Crosshouse Hospitals under each of the options for the future delivery of acute care in Ayrshire and Arran. The advantage of simulation modelling is that it enables the testing of a number of assumptions to inform decision-making.

The simulation models presented provide a sound basis for refinement and development of a model that can be used to inform the implementation phase of the review of services project. Using the model the required number of beds can be calculated and tested using differing triage data that will aid the implementation phase.

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AN AGENT-BASED SIMULATION MODEL OF MRSA TRANSMISSION IN HOSPITAL

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ABSTRACT

MRSA is a major challenge to health care systems in that it is a significant cause of hospital acquired infection. There are a variety of strategies for reducing MRSA transmission in the hospital, particularly rapid detection, isolation, and decolonisation treatment of patients. Current models of MRSA transmission apply stochastic mathematical techniques sometimes coupled with Monte Carlo simulation. We present the first use of an agent based simulation to describe MRSA transmission, which focuses on local agents and their interaction with each other and the external environment which was developed, using Anylogic® . Simulation was carried out using data derived from expert opinion, the literature and hospital activity data. In the simulation, length of time to test report and length of stay had the greatest influence on transmission rates and numbers of secondary cases.

Keywords: MRSA, Agent-based simulation, Infection control, Modelling

1. INTRODUCTION

Methicillin resistant *Staphylococcus aureus* (MRSA) is a major cause of secondary infections, and is endemic within hospitals in the United Kingdom. One of the keys to control is identification of patients followed by the implementation of a series of infection control precautions. These include isolation of the patient within a side room to reduce cross transmission and the use of decolonisation treatment to reduce the colonisation burden.

The simulation is designed to test the effectiveness of different procedures for the control of MRSA, including whether a rapid molecular test using polymerase chain reaction (PCR), which provides results in two hours is more effective than the established slower culture based test. The modelling was part of a study which took place in Birmingham (1). It was a two-period cross-over study in seven surgical wards.

Most existing MRSA modelling studies apply stochastic mathematical modelling techniques (2,3,4,5,6,7,8) and many are coupled with Monte Carlo simulation (2,3,6,8). Some studies focus on a single ward level (5,6,8), others, at the hospital level (2,3,4,7), while some also include the external community (3,4). All existing studies assume direct transmission between patients or indirect transmission by transiently or persistently colonised health care workers (HCWs). Some model this interaction directly (5,6,8) and some indirectly by formulating the risks to the MRSA negative patients (the "mass action" assumption) (2,3,4,7). The models have restrictive assumptions in order to fit with the requirements of the underlying mathematics, most assuming, for example, 100% ward occupancy and a negative exponential distributed length of stay.

This paper describes a novel approach in which we apply agent based simulation to MRSA transmission. Agent-based simulation focuses on the behaviour of individual local agents and their interaction with each other and with the external environment (9,10,11). This seemed particularly appropriate for modelling the transmission of MRSA in hospital where the status of particular individuals affects the status of other individuals within the environment of a ward bay and within the wider environment of the whole ward and beyond

Models were developed in Anylogic®, which is commercially available, to replicate the assumptions and results of two very different models in the literature (4,6). One was a hospital level model using mass-action assumption (4) and the other a ward-level model explicitly including HCWs (6). The agent based simulations were found to be relatively slow but they replicated the results in the papers well.

We decided that the simulation for this study should be ward based and have the capability of modelling the admissions, the location of the patients in the ward, lengths of stay and screening. Since it is difficult to ascertain the extent to which HCWs are colonised and the frequency with which they cause transmission to MRSA negative patients, we decided not to model them explicitly. The modelling approach is an adaption of the mass-action assumption in which transmission is dependent on the number and location of colonised individuals. The main output from the simulation is the number of patients who are MRSA negative on admission, who become colonised during their stay.

2. MODEL DESCRIPTION

2.1 PATIENT STATUS

The structure of the simulation is that there are two main state charts that are constantly monitored: one describes the MRSA status and the other the patient's physical location. If patients change their MRSA status (Figure 1), they change their risk to other patients on the ward. Those who are undetected positive will be the greatest risk to other patients because no precautions are taken. Once MRSA is detected, a patient is subject to decolonisation treatment which reduces their risk and may return them to MRSA negative status.

A patient identified as MRSA positive is assumed to be isolated if there is an isolation bed available. The location status (Figure 2) of the patient indicates whether the patient is: in isolation or in a ward bay (the study wards have from three to five bays).

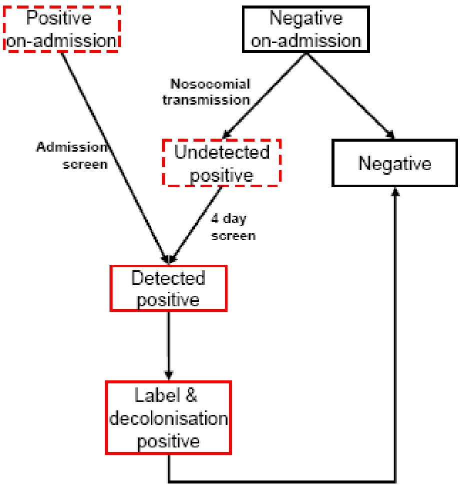

Figure 1: MRSA status and transition

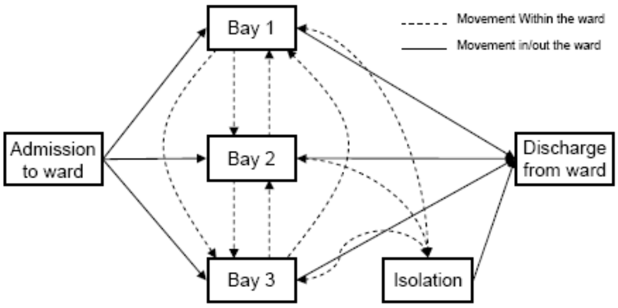

Figure 2: Patient location status and movement, the patient may move between the bays.

Patients arrive in the ward randomly and their length of stay is sampled from a distribution. A patient may move between the bays and will be discharged when the sampled length of stay is complete. At any specific time during a patient's stay in the ward, the patient must be in only one MRSA state and only one location state.

2.2 PATIENT SCREENING

When patients are screened, there is a delay before the reporting of the result which depends on the type of test. Rapid PCR testing (less than 18 hours) versus conventional culture (from 24 to 72 hours).

The model has three different states for patients with regards to MRSA colonisation: (1) patient has a negative MRSA status, (2) patient is colonised with MRSA, but is undetected (3) patient has been identified as being colonised with MRSA. Those patients admitted with an MRSA negative status are vulnerable to colonisation. If the patient becomes colonised with MRSA, their status will first change to undetected positive whilst their next screen test is awaited, then to detected positive once the result is known.

Secondary transmission will be detected through the repeated screening of patients during their admission. The screening tests are assumed to be 100% sensitive. Patients who are identified as being colonised with MRSA will receive decolonisation treatment and will be isolated if possible.

2.3 SECONDARY TRANSMISSION

In the model, every MRSA negative patient has the potential risk of becoming colonised. The transmission risk of every negative patient is re-evaluated when:

- A positive patient enters or leaves the bay.
- A negative patient in the bay becomes positive.
- The status of an existing positive patient changes.

The risk comes from the presence of the positive patients in the ward. The risk to the negative patients is in two parts:

- From the proximity of positive patients in the same bay;
- From positive patients in the whole ward, including isolation, thus allowing for the movement of individuals between different parts of the ward.

The model also takes account of the environmental reservoir of MRSA (e.g. the bed, linen, lockers or other equipment) and assumes that the risk from a positive patient remains for 12 hours from when they left the bay or ward.

The equation used for calculating the transmission probability is adapted from the mass action assumption (3,4). The main modification is to distinguish the source of transmission risk by introducing the parameter *m* so that *m* proportion of transmission risk comes from within the same bay while the remaining risk comes from the whole ward. The rationale for treating global and local contacts differently, when studying stochastic infection transmission, is discussed in detail in by Koopman *et al.* (12). Another modification is to reduce the risk of treated positive patients, as opposed to untreated positive patients, differently by introducing parameter k. The basic equation is as follows:

$$T_{ij} = T\left[m\frac{u_i + kd_i}{n_i - 1} + (1-m)\frac{(u+kd)}{n-1} \right]$$

Tij: Probability that a negative patient j in bay i becomes colonised in one day
T: Transmission ratio per day for an undetected positive patient in an infinite population
ni: Number of patients in bay i
u_i: Number of undetected positive patients in bay i
di: Number of detected positive patients in bay i
n: Number of patients in the whole ward
u: Number of undetected positive patients in the whole ward
d: Number of detected positive patients in the whole ward
k: Effect on reducing transmission by labelling and decolonising a positive patient where k is between 0 and 1
m: Proportion of risk coming from contact within the bay

Some patients are more vulnerable to becoming colonised. These include those with an intravenous device and those who have been to ITU. Suppose V_j is multiplying factor for patient vulnerability where "normal" patients have a vulnerability of 1. The adjusted equation which considers vulnerability is as follows:

$$T_{ij} = TV_j\left[m\frac{u_i + kd_i}{n_i - 1} + (1-m)\frac{(u+kd)}{n-1} \right]$$

2.4 MODEL STRUCTURE

This proposed agent-based simulation model consists of three hierarchies or abstract levels. The highest abstract level only contains replicate agents (i.e. patients) and the global variables (i.e. input parameters as well as variables collecting system information).

The middle abstract level represents each individual patient agent and some local variables defining the attributes of each agent. This level also defines the state-charts.

The lowest abstract level defines the detailed behaviour of an agent via the state-charts. The state-chart contains all the possible states of an agent and defines how the agent could transfer from one state to another.

2.5 MODEL INPUT

The parameters (Table 1) were derived from the literature or local expertise and hospital activity data.

Table 1: Input needed for model testing, in addition to the values in the equation

Number of beds in ward
Number of bays
Number of isolation beds
Test response time (days)
Mean length of stay (days)
Mean patient arrival rate per day
Proportion of colonised patients admitted
Proportion patients screened on admission
Repeated screen interval (days)
Proportion of patients decolonised
Decolonisation delay (days)
Decolonisation treatment duration (days)
Decolonisation success rate
Proportion admitted to ITU
Proportion using intravenous device
Environment delay (days)
Occupancy of isolation beds (MRSA)

3. RUNNING THE MODEL

3.1 MODEL VALIDATION

The model is to be tested with data from seven surgical wards and each cross-over period.
These parameters are:

- Those with the same values throughout (e.g. basic transmission coefficient).
- Those unique to each ward. (e.g. ward layout information)

- Those unique to each ward and cross-over period (e.g. length of stay).

In the validation we will compare the number of secondary colonisations, based on observation, with the number of secondary colonisations predicted by the model (using 100 iterations of the simulation) for each ward and cross-over period

3.2 TEST SCENARIOS

Table 2 summaries the setting and key results of the what-if analyses, using the input data described above..

4. DISCUSSION

Using the simulation and the test data set, it appears that it is beneficial to have a fast test response time, to screen patients frequently and to have a few isolation rooms dedicated to MRSA colonised patients. Shorter lengths of stay were found to be associated with higher transmission rates. The number of transmissions was found to increase with an increase in the number of colonised patients admitted but the transmission ratio was found to go down. This was because of the limited number of MRSA negative patients, who could be present in one ward.

The use of agent based simulation is an exciting development which is both powerful and flexible. It represents individual patient agents with two state charts which locate the simulated patients in space also and identify their MRSA status and whether detected and treated or not. Patient agents are able to interact with their environment and respond when new patients are admitted or discharged from the ward or bay. We can give the patient agents characteristics which describe, for example, the vulnerability of individual patients to colonisation and to take their location in the ward into account in determining their likelihood of being contaminated by other patients.

Unlike the mathematical and system dynamics models, it is possible to sample from any distribution facilitating the realistic modelling of, for example, lengths of stay. Agent based modelling is a flexible approach that is more transparent than mathematical modelling and can be adapted to different ward configurations and new research data.

There is clearly further work to do in running the simulation with the final data from the trial (1) and in validating the model for use. Further sensitivity analysis will be applied to test the robustness of the assumptions made.

Table 2: Summary of simulated test scenarios based on the test data in Table 1.

Factor	Factor setting	Secondary cases range (mean)	Transmission ratio range (mean)	Secondary cases	Transmission ratio	Remarks
Test response time (days)	0.5 to 4	23.0 to 38.1	0.36 to 0.61	Increase	Increase	
Repeated screen interval (days)	1 to 7	27.1 to 31.7	0.43 to 0.5	Increase	Increase	
Proportion of colonised patients admitted (%)	1% to 21%	9.3 to 134.6	0.48 to 0.35	Increase	Decrease	
Isolation beds (bed)	0 to 8	37.1 to 30.7	0.59 to 0.48	Decrease	Decrease	Smaller proportion of colonised patients admitted
		84.8 to 78.3	0.49 to 0.42	Decrease	Decrease	Larger proportion of colonised patients admitted
Mean length of stay (days)	2 to 10	39.8 to 25.8	0.20 to 0.64	Decrease	Increase	Ward occupancy keep constant, patient arrival rate varies
	2 to 7	11.9 to 30.9	0.19 to 0.51	Increase	Increase	Patient arrival rate keep constant, ward occupancy varies
Mean ward occupancy (%)	50% to 100%	16.4 to 30.9	0.50 to 0.47	Increase	Stable	

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DGHPSIM: PERFORMANCE MODELLING OF GENERAL HOSPITALS

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ABSTRACT:
In this paper, we discuss the development of a generic suite of simulation models that can be parameterised to show the performance of general hospitals in England with respect to waiting times. The models can be parameterised to suit particular hospitals using both nationally available data and data collected at each hospital. The models are intended to allow hospital managers to experiment with different approaches to performance improvement and also regulators to assess the likely performance of hospitals. The aim is to add quantitative insights to the qualitative debate in which policy is often formed.

Keywords: Simulation, Healthcare Applications

1. INTRODUCTION

Access to adequate healthcare is widely regarded as a human right, yet such access is restricted in all countries, since the demand for healthcare seems limitless. In some countries, notably the USA, access is rationed by a price mechanism; which means that some people, unable to finance their healthcare directly and unable to afford insurance, may be unable to gain adequate access. In other countries in which most healthcare is publicly funded, notably the UK, access to some parts of the system, especially for hospital care, is rationed by several mechanisms, including waiting lists. However, even from the early years of the NHS there has been widespread concern that waiting times were too long (Appleby et al, 2005; Yates (1987). When the UK Labour government was elected to power in 1997 it promised to reduce waiting times which, by common consent, had grown too long. To do this, it introduced a target-based regime in which healthcare providers are required to meet waiting time targets, which have grown more stringent over the years. This paper is concerned with the target regime in England, which has been more ambitious and backed with stronger sanctions than comparable regimes in Scotland, Wales and Northern Ireland (Bevan, 2006; Bevan and Hood, 2006).

The increasing stringency of the targets is exemplified in table 1, which shows those in place for two groups of patients. These are patients waiting for hospital admission as an inpatient, after the decision has been made that admission is required, and those waiting for an outpatient appointment after referral by a GP. At the time of this paper, NHS Hospital Trusts are struggling to meet the 18-week RTT (Referral to Treatment) target by the end of 2008. The 18-week RTT target requires that no patient wait any longer than 18-weeks from the time of their GP referral for admission as an inpatient. In effect, this means that the 2005 inpatient admission target of 6 months (26 weeks) has been reduced to about 9 weeks, which is all that is left if 9 weeks are needed for outpatient referral and diagnosis. This is a very severe reduction and is concentrating the minds of many healthcare managers.

This paper discusses some simulation modelling conducted as part of the DGHPSim (District General Hospital Performance Simulation) project, which aims to develop generic simulation models of hospital activity. The models are generic in the sense that their logic should fit a wide range of general hospitals and can be customised for particular hospitals using data specific to that hospital. The relevant data comes from two main sources:

Table 1: Historic inpatient and outpatient waiting time targets.

Patient waiting time target	2001/02	Mar. 2003	Mar. 2004	Dec. 2005	Dec. 2008
Outpatient appointments	26 weeks	21 weeks	17 weeks	3 months	18 weeks (for whole journey)
Inpatient admissions	15 months	12 months	9 months	6 months	

1.HES (Health Episode Statistics), which are collected nationally from all UK NHS hospitals and cover all admissions for inpatient or outpatient care. The HES datasets allow the tracking of all anonymised patient journeys in UK hospitals, at the outpatient and inpatient stages separately.

2.Data collected by the hospital itself and not required for HES or similar national schemes. These cover, for example, the number of beds available and historic data such as existing waiting lists.

2. THE DGHPSIM MODELS

There are four models in the DGHPSim suite and these are can be run independently or linked together. They are conceptualised in figure 1 and are as follows:

1.Accident and emergency: this simulates the arrival of patients from the outside world into a typical A&E unit, their care in the unit and subsequent discharge or admission for emergency inpatient care.

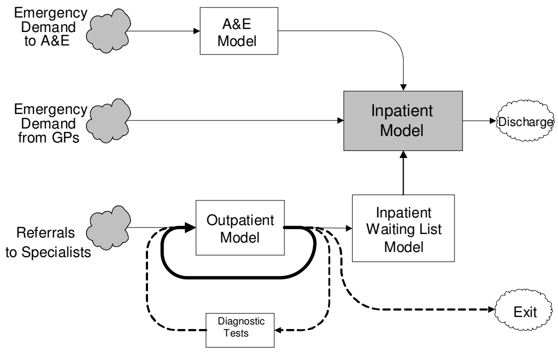
2.Outpatient care: this takes GP referrals for outpatient care and generates a sequence of appointments using a system of diaries, which can be used to model outpatient waiting lists and waiting times. When their clinic slot arrives, the model takes patients from the outpatient waiting lists and simulates the provision of their care through several stages including diagnostics. Many of these patients will be discharged after outpatient care, but some will require inpatient admission.

3.Inpatient waiting list model: patients who require inpatient admission are placed on actively managed inpatient waiting lists that distinguish between severity of cases.

4.Inpatient model: this simulates the treatment of patients as inpatients, these coming from the inpatient lists, emergency admissions from A&E and direct emergency referrals from GPs.

Each of these models is now discussed in more detail. All are developed using the Micro Saint Sharp simulation software (Micro Saint Sharp, 2007), which is well-suited to simulating service systems. In a parallel project based in Spain, some of the models are being ported to run in Java, to see if this has any advantages, such as portability.

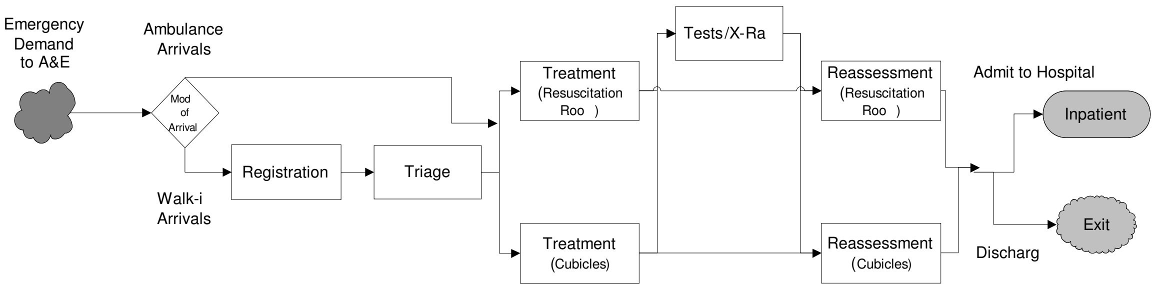
Figure 1: DGHPSim Models – A conceptual representation.



1.1 THE ACCIDENT AND EMERGENCY MODEL

A detailed account of this model can be found in (Gunal and Pidd (2006)) and it is very similar to other A&E models developed elsewhere (Blake and Carter (1996), Fletcher et al (2006)), with the exception of modelling multitasking medical staff. It was built to gain the confidence of the hospital acting as the main development site for the DGHPSim project, though it was known at the time that it would have been possible to re-use one of the existing models. The structure of the model is shown in figure 2. Patients arrive stochastically from the outside world, using sampling routines that reflect within-day and within-week variation. On arrival, walk-in patients are registered and may be subject to triage using the Manchester system (Manchester Triage Group (2005)) to determine their urgency. Patients arriving by ambulance do not need to be registered or triaged. Patients then wait for treatment in a cubicle. They may also be sent for tests and further treatment, following which they may be discharged or admitted as inpatients. Since doctors and other staff are known to see multiple patients simultaneously (Chisholm et al (2000)), the model represents this as multi-tasking. The model provides various performance indicators, of which the one of most concern, at the moment, is the time taken from arrival to discharge or admission – currently, this should not exceed four hours.

Figure 2: DGHPSim A&E Component Model.



1.2 THE OUTPATIENT MODEL

One role of GPs is that they act as gatekeepers for specialist care, referring to outpatient clinics those patients whom they think need to be seen by a specialist, possibly for ultimate admission as inpatients, but initially as outpatients. Historically, this involved the GP writing a referral letter to a particular specialist after discussion with the patient. This is now changing in two ways. First, the communication may be via e-mail or a similar medium. Secondly, increasingly, referrals now made to a healthcare provider (NHS provider Trust) that decides which specialist will see the patient and where they will be seen, if the Trust operates on more than a single site. Once accepted on a specialist's list, the patient is given an appointment for an outpatient clinic some time in the future.

There are known to be many different ways in which specialists book patients for appointments. However, insofar as referral is now to a Trust and not directly to a specialist, it seems likely that there will be greater uniformity. Hence, the model books patients onto a list for each speciality rather than each specialist. These grouped lists are managed as follows.

- The list consists of a number of slots each week.
- A proportion of the slots are allocated to follow-ups and a proportion to new patients.
- New referrals are divided into 2 groups: urgent and non-urgent. Urgent patients are booked in the first available slot; non-urgents are booked into the first slot beyond a definable time window.
- Follow-ups are booked into the diaries like non-urgent new arrivals, but to follow-up slots.

Since hospitals have existing waiting lists which are, in effect, backlogs for treatment, the models assume that the user will define this backlog, providing the starting conditions for the simulation.

Most outpatient clinics deal with 3 classes of patient: GP referrals, follow-ups from outpatients and follow-ups from inpatients and these are represented in the model with very similar behaviour. When the time for their clinic arrives, the model takes the outpatients from the waiting list slots and simulates their interaction with a specialist. As a result of this interaction, they may be discharged, or may require admission as an inpatient, another outpatient appointment or diagnostic tests, following which a further outpatient appointment may be required. Patients who require further outpatient appointments are re-booked into the diaries.

1.3 INPATIENT WAITING LIST MODEL

Waiting lists and waiting times for inpatient admission have been a major focus of government targets in the UK, as shown in table 1. Since the management of these lists can become rather complex, the DGHPSim suite includes a model that represents the management of these waiting lists for elective admission. It is important to realise that these lists do not operate as simple FIFO queues (Mullen (2003)) but patients are moved around the lists to ensure that urgent patients have priority and that no patient waits too long. The latter condition means that a simple urgency-based queue will not work, since non-urgent patients will always remain at the end of such a queue. The model works by awarding each patient who requires admission a priority score based on their condition and thus assigns them an

Figure 3: Ward Transition Matrix for General Medicine, Emergency patients.

	General Medicine - Emergency								
		Wards							Discharge Gate
		GMED	GSUR	GCRI	GSPE	GELD	GWOC	GASM	
Wards	Entrance Gate	0.069	0.002	0.080	0.001	0.001	0.001	0.846	
	GMED	0.090	0.052	0.011	0.007	0.069	0.021	0.003	0.746
	GSUR	0.034	0.086	0.022	0.003	0.037	0.015		0.802
	GCRI	0.357	0.025	0.016		0.007		0.032	0.564
	GSPE	0.135	0.054		0.135	0.027			0.649
	GELD	0.043	0.017	0.009		0.088		0.009	0.835
	GWOC	0.010	0.031			0.010	0.041		0.907
	GASM	0.525	0.025	0.019	0.003	0.052	0.006	0.012	0.358

initial position in the list. As they wait in the list, this priority score is increased to stop non-urgent patients remaining at the end of the list.

1.4 INPATIENT MODEL

Inpatients are admitted to a hospital bed in a ward and under the care of a particular speciality. Whilst in hospital, they may move wards and change specialties, though the vast majority of inpatients stay in the ward and specialty to which they are admitted. The data from hospitals' Patient Admission System (PAS) datasets allow the estimation of the probabilities of such moves and changes and this is used as the basis of ward transition matrix. Hence, in the model, patients are admitted to a ward and may, during their stay, move or change as governed by the transition matrix. An extract from such a matrix is shown in figure 3. Wards can also be grouped to reduce the size of these matrices. Duration of stay of patients in each ward is modelled using stationary distributions, for each specialty and for elective and emergency patients separately.

As mentioned earlier, inpatients are admitted by 3 routes: from elective waiting lists, as direct emergencies or from A&E. The model works on a daily basis, as follows:

- It accepts emergencies from direct referrals or from A&E and these occupy beds.
- The remaining beds are used to take patients off the elective lists, depending on the specialty and the day of the week. Thus, the number of elective patients admitted to a ward on a day will vary.

This is a simplification of how the admission system works in practice, since patients on the elective waiting list are actually given an admission date in advance by assuming how many emergencies will be admitted. If there are not enough beds available on the day because too many emergencies are admitted, affected elective patients are given a new date as soon as possible – that is, they are returned to the list. The approximation used in the inpatient model seems to produce the same result.

The model assumes that there is always enough theatre capacity for surgery, on the reasoning that surgical capacity is rarely the constraining resource for general hospitals (Healthcare Commission, personal communication). That is, theatres are not represented in the model and are assumed to be sufficient to support the number of beds. Length of stay of patients in each ward is modelled using stationary distributions, for each specialty and for elective and emergency patients separately. The distributions and parameters are estimated using hospitals' PAS datasets, since the HES dataset has no detail of patients' physical bed usage.

3. USING THE DGHPSIM SUITE

As noted earlier, a problem which ails many healthcare systems is that of excessive waiting times. Historically, the UK's NHS has suffered from this problem to an acute degree. Also, as stated earlier, the British government has staked a huge amount of political capital on the transformation of the English NHS from a cheap high-wait system to an expensive low-wait system.

Underlying this drive there are two interlinked questions:

1. For a given investment what level of waiting can be delivered?
2. What advice should be given to hospitals seeking to achieve performance?

The answer to these questions is not obvious, as the relationship of waiting to resourcing is non-linear (twice the investment does not imply half the waiting time). Moreover, hospitals are complex systems dealing with stochastic demand flows and actions which often appear sensible when viewed in the context of one specialty (e.g. carving out bed space for patients with a particular condition) can often appear less sensible when viewed from the point of view of the interests of the organisation as a whole.

The DGHPSim suite may be used to explore a number of questions, such as:

- Given this hospital's level of resourcing, what sort of performance characteristics (length of stay, use of day case surgery) would be required for it to meet the 18 week wait target?
- Given this hospital's performance characteristics, what sort of level of resourcing would be required for it to meet the 18 week wait target?
- Since hospitals are required to hold buffers against peak and emergency demand, how does performance against elective targets trade-off against targets for emergency admissions? And within the elective wait, how does performance against waits for those whose journey stops as outpatient trade-off against those whose journey goes right up to inpatient admission?
- The development agency for the NHS, the Institute for Innovation and Improvement makes a number of recommendations (e.g. concerning combining queues and outlying patients) which will have an impact on waiting time performance. Are these impacts substantial or are they dwarfed by uncontrollable factors (e.g. seasonal fluctuations in demand)?

The DGHPSim suite enables us to add quantitative detail to the qualitative insights on which policy is too often based, and provide useful advice both to those responsible for setting targets, and for those whose role is to help hospitals achieve higher levels of performance. We conclude that there is a role for Discrete Event Simulation in any healthcare system which seeks to follow the lead provided by the English system in tackling this persistent problem.

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