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DO HYBRID SIMULATION MODELS ALWAYS INCREASE FLEXIBILITY TO HANDLE PARAMETRIC AND STRUCTURAL CHANGES?

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ABSTRACT

Are hybrid simulation models always beneficial? When should one modeling paradigm be used more than another? How does one know the right balance has been reached between different simulation techniques for the system under investigation? We illustrate selected insights into hybrid simulation through the use of a discrete event simulation (DES) model and a hybrid DES agent based model (ABM) of the obstetrics department at Akershus University Hospital. Design decisions are not straightforward, and have different impacts on model development and ability to address different scenarios or potential changes. In the DES model, the majority of the logic and code representing patient pathways is contained within the structure of the model. In the AB-DES model, a selection of the code is shifted from the model structure to the patient entities. Scenarios are presented which illustrate strengths and weaknesses of each model. These are reflected on and future work is suggested.

1 INTRODUCTION

The Health Services Research Unit (HØKH) is based at Akershus University Hospital (Ahus) Norway. HØKH is clustered around three overarching themes, organization and user perspectives, operational analysis, and system improvement. HØKH takes a multidisciplinary approach to studying health services, and holds expertise in medicine, health economics, organizational theory, medical sociology, anthropology, statistics, and mathematical modeling.

HØKH were approached by staff from the obstetrics department in June 2014 with a request to investigate the flow of mothers through the clinic. A series of workshops were held which will be discussed in greater detail in section 2.2. Simulation models were used to analyze the patient flow and organization of the department to identify bottlenecks and areas with potential for improved resource utilization. The purpose of the paper is to compare a hybrid agent based discrete event (AB-DES) model with a DES model of the same system the obstetrics department.

The remainder of the paper is split into seven sections. Section 2 sets the paper in the context of other hybrid simulation modeling work and provides more detail about the obstetrics department. Section 3 summarizes the data collection, processing and analysis that were undertaken to provide data for the models. Section 4 describes the models that have been developed for this paper. Section 5 presents three hypothetical scenarios used to evaluate the models. Section 6 presents selected scenario findings. Section 7 evaluates how the two models addressed the scenarios. Section 8 highlights selected methodological considerations and concludes with suggestions for future research.

2 BACKGROUND AND CONTEXT

2.1 Background

There are many different simulation models presented at the winter simulation conference ranging from practical implementations to the purely theoretical. The models range from those produced using commercial packages to bespoke models coded from scratch in a variety of programming languages. The models are typically implemented within an agent based modeling (ABM), discrete event simulation (DES) or, to a lesser degree, system dynamics (SD). For more details about these approaches, see (Brailsford et al. 2014; Law 2009, Zeigler et al. 2000; Sterman 2000). A taxonomy of model approaches produced by Brennan et al (2006) categorized models usefully by interaction allowed and by the level of the model i.e. aggregate or individual level. Does it matter which type of modeling technique is used? Brennan et al (2006) state that you should use the simplest approach to address the problem. Tako and Robison (2009) demonstrated that users of models didn't care which approach is used, provided they gained insight into the system being modeled, i.e. that it was perceived as useful.

Hybrid simulation seeks to utilize continuous and discrete simulation approaches at the same time to model situations exhibiting a mix of continuous and discrete components. There has been debate about the philosophical and technical difference between the continuous and discrete simulation approaches (Brailsford et al. 2010). Many conceptual frameworks of how continuous and discrete approaches could be combined have been produced. Lorenz and Jost (2006) developed a framework for combining DES, ABM and SD which stressed the purpose of the model as the key factor in deciding which modeling approaches should be applied. Chalal and Eldabi (2010) proposed a framework detailing how and why to combine SD and DES models in a healthcare context. A complimentary framework for combining DES and SD in a healthcare context was illustrated with the use of a radiotherapy case study by Morgan, Howick and Belton (2011).

Other relevant hybrid modeling examples include Djanatliev et al. (2012) SD-ABM model of health care technology assessment of stroke technology in which they promoted and evaluated the concept of loosely coupled models. In an SD model of chlamydia screening and transmission in the UK to assess screening strategies, Viana et al. (2014) nested a more detailed DES sub-model to assess treatment constrains on screening strategies. Zulkepli et al. (2012) developed a DES-SD hybrid to investigate an integrated care model, emphasizing the interface between the different modeling paradigms/levels. Viana et al. (2012) produced an ABM-DES-SD model to assess the effects on the health and social care system in the UK attributed to age related macular degeneration (AMD). The frameworks and case studies presented show that the combination of approaches can produce symbiotic realizations of the strengths of the individual techniques, while reducing their limitations. This is assuming that they are combined appropriately. Rossiter (2015) stresses that use of best practice ideas from software engineering, when developing simulation models. In his paper the AMD model (Viana et al. 2012) is used as a case study.

This paper compares the use of a DES model with an ABM-DES model of the obstetrics department at Ahus University Hospital. The paper will reflect primarily on the technicalities of model development rather than the practical implications for the department. It will highlight the functionality that can be achieved in the AB-DES model which cannot be achieved in the DES model.

2.2 Context

The obstetrics department at Ahus approached HØKH to help them understand the flow of mothers through the department. They wanted to understand if resources could be better utilized, to identify bottlenecks, and to explore different configurations of the department in a safe environment. The obstetrics department consists of five wards. There are two delivery wards, ward A for natural births (uncomplicated) and ward B for births requiring epidurals, caesarians, or inducement (complicated). There is an observation ward (observation) which is used for pre or post-delivery, and the maternity ward (maternity) is used for those requiring more observation than at a regular hospital bed. Additionally, there is the "patient hotel", with regular ward beds for mothers with no complications. Figure 1 was produced in the workshops during the problem structuring phase. It illustrates the main flow through the system (the patient pathway).

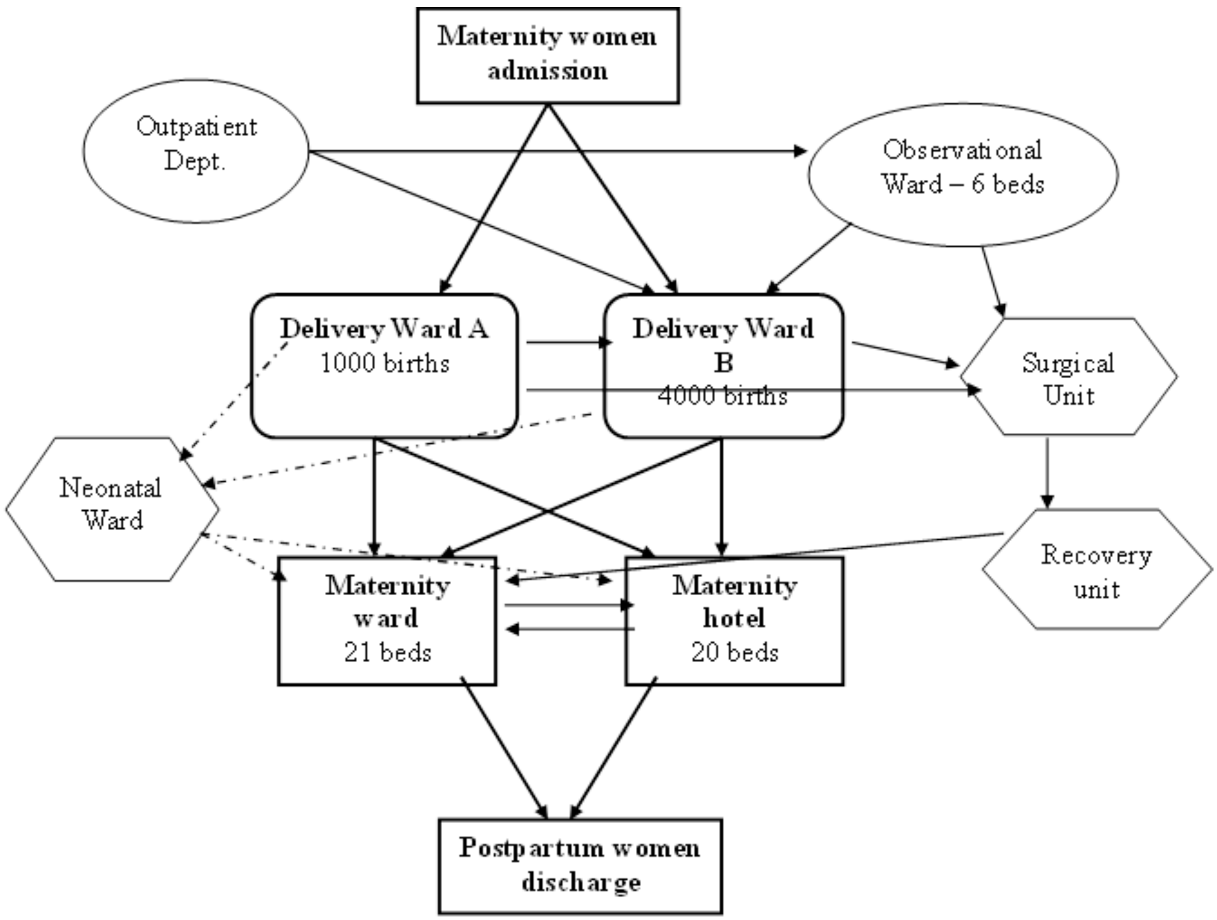

Figure 1: The obstetrics department (the system) described during workshops.

A series of workshops were undertaken with the department to ascertain the scope of the model, the scenarios and alternative configurations of interest. There was interest in achieving an efficient flow of mothers through the department, without sacrificing human proximity. Examples of questions that the model could address included: more flexible sharing of staff between the two delivery wards, increasing the capacity of observation ward, strategically controlling the timing of induction, etc. DES was chosen as the main approach to represent the system. Figure 2 provides the conceptualization of the two models that were developed to address the questions. Initially a typical DES model was produced (see the left hand side of Figure 2), but during the model development it became apparent that patient pathways were more varied than anticipated, which might be more easily handled by giving some agency to the patient entities. Therefore, a hybrid AB-DES model was produced (see the right of Figure 2).

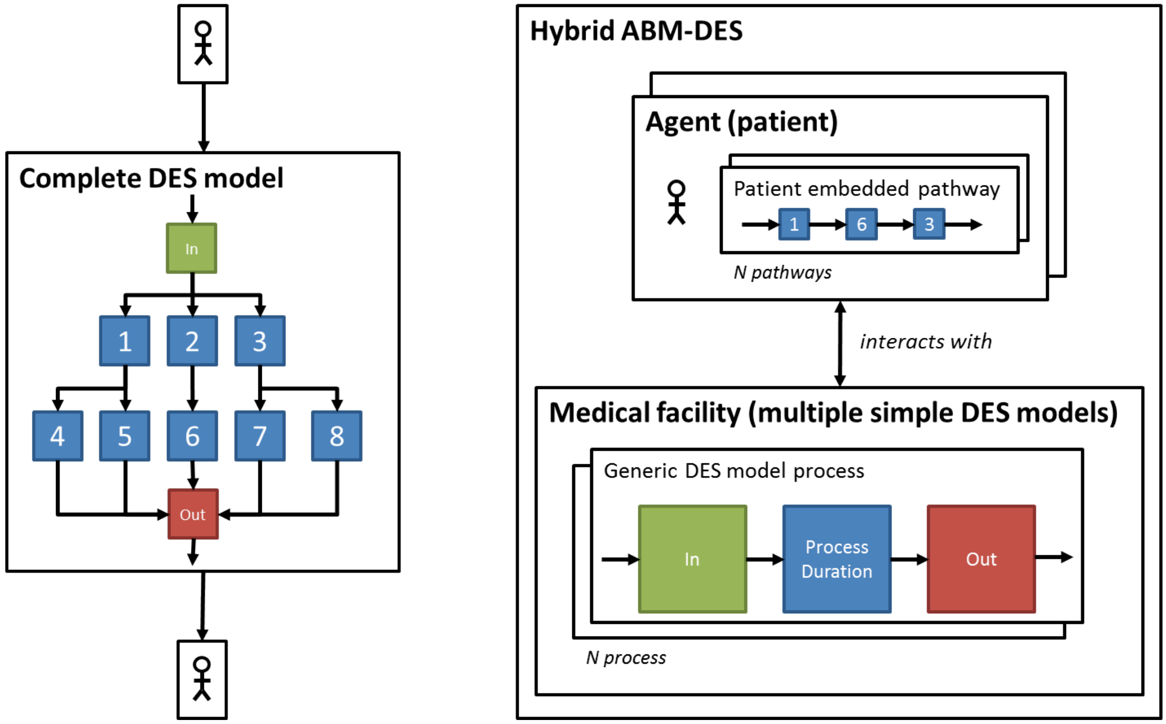

Figure 2: Model conceptualization, DES model (left) and AB-DES model (right).

3 DATA

The model runs for one year. Data relating to admissions from 2014 were extracted from hospital record systems and analyzed using R (A Language and Environment for Statistical Computing). As some patients in the ward in 2014 were admitted in 2013, and some admitted in 2014 remained in the department into 2015, the data covered the period 22/12/2013 to 22/01/2015. There were 5,727 unique arrivals, or "visits", the point of entry to the department. The breakdown of visits by ward is illustrated in Table 1, which also provides the capacity of each of the wards and its technical name which is used in the model.

Table 1: Ward capacity and ward of entry "visits" to the department in 2014.

Ward	Name	Visits (Entry ward to department)	Capacity
Normal delivery	B405_A	1361	8
Complicated delivery	B405_B	3421	16
Observation ward	S405_A	758	6
Maternity ward	S405_BCD	142	21
Patient Hotel	NNBAR	35	20

The arrival pattern profile (the seasonality) of the visits by ward were also investigated. Figure 3 provides an example of the seasonality for the examination ward. In July the examination ward was closed hence zero visits in July.

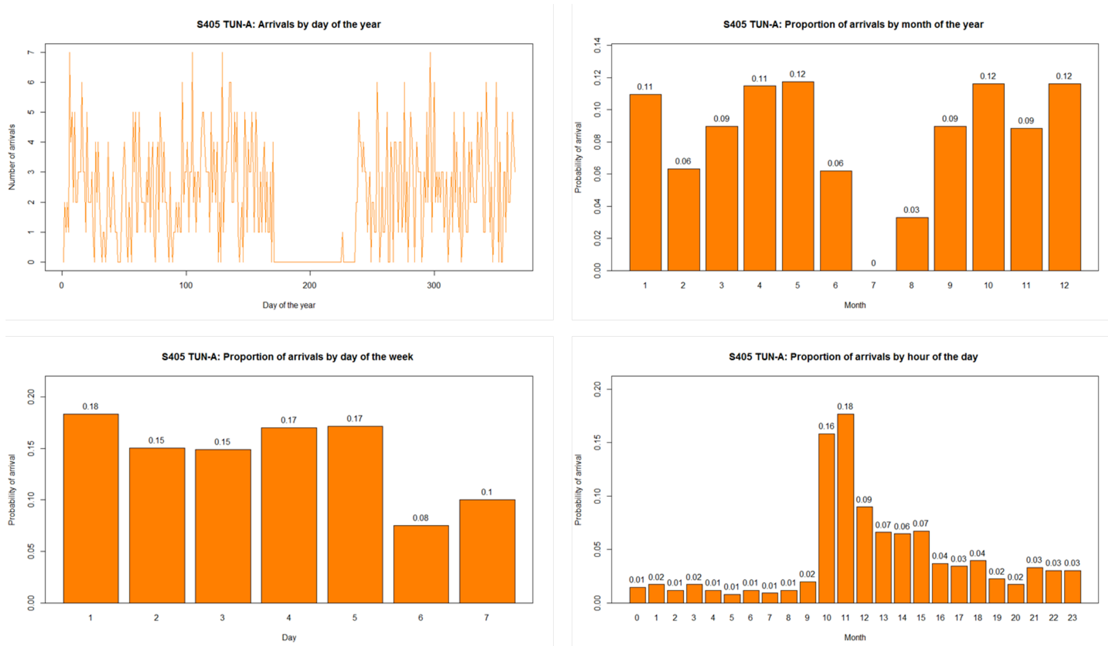

Figure 3: Visit patterns for the observation ward by month, day and hour.

A visit typically consists of multiple episodes. We define a patient episode as a period defined by the patient being in one of the wards. When a patient moves to a new ward or changes a bed in a ward, a new episode begins. There were 12,119 episodes during 2014. Data for each episode were extracted from hospital systems, consisting of the ward the episode related to, the start and end times for the episode and a unique non-identifiable reference number for the patient. In 2014 the number of episodes per visit was distributed as follows: one episode (11.72%), two episodes (68.53%) three episodes (16.28%) four or more episodes plus (3.47%). In most cases the expectant mother arrived to give birth and then stayed in either the maternity ward or patient hotel before returning home. There are other reasons to visit the department, such as checkups pre- and post-delivery, and multiple episode can also be explained by complications such as preeclampsia, diabetes, or infant related issues. The transition probabilities of moving between wards are provided in Table 2. These were used to represent the pathways through the models. It is possible to move between beds in the same ward hence the small probability of moving to the same ward.

Table 2: Probabilities of moving from "From" ward to "To" ward after the patients sampled length of stay (LoS may be stochastic or deterministic). Possibility of changing bed within the same ward.

		To						
		B405-A	**B405-B**	**NNBAR**	**S405-A**	**S405-BCD**	**Home**	**Total**
From	**B405-A**	0.07%	2.47%	60.28%	4.52%	21.48%	11.17%	100.0%
	B405-B	0.00%	1.30%	43.50%	5.29%	44.63%	5.27%	100.0%
	NNBAR	0.13%	0.10%	0.49%	0.13%	1.95%	97.21%	100.0%
	S405-A	4.20%	59.31%	2.58%	0.10%	3.92%	29.89%	100.0%
	S405-BCD	0.21%	0.91%	14.03%	0.00%	0.87%	83.99%	100.0%

Empirical distributions reflecting the length of stay (LoS) by ward were fitted using the "fitdistrplus" package in R. The fitted distributions are provided in Table 3. Where data were normalized in order to fit theoretical distributions maximum length of stay has also been stated. There were a number of episodes/visits which had very long LoS, e.g. 971 hours (40+ days) these were checked individually with department staff.

Table 3: Fitted length of stay (LoS) distributions by ward.

Ward	Distribution	Parameters	Maximum (hours)
B405_A	Gamma	Shape = 0.260, Rate = 9.467	571
B405_B	Gamma	Shape = 0.351, Rate = 16.434	721
S405_A	Gamma	Shape = 0.358, Rate = 8.614	971
S405_BCD	LogNormal	Mean log = -2.625, SD log = 0.610	857
NNBAR	Logistic	Location = 44.367, Scale = 8.752	118

The data discussed in this section was used in both models, no additional data were collected. The raw data relating to the 12,119 episodes was used in the data driven model discussed in the next section.

4 MODELS

Two models were created in AnyLogic, a DES model and an AB-DES model. In the DES model, the patients were represented by passive entities. We placed all of the logic in the structure of the system, the patient pathway. The AB-DES model can be run in two separate modes, 1) *stochastic mode*, used when evaluating "what-if" questions, or ii) *deterministic mode.* The deterministic mode, which can be used to verify certain properties of the model and the source data, will be explained in more detail later.

4.1 The Discrete Event Simulation Only Model

Based on the workshops with the department staff, a DES model seemed like a good starting point. In this model, the patient is a passive entity passing through the wards in the maternity department based on routing probabilities at different points of the pathway. Figure 4 illustrates the DES model, with a model visualization shown on the left and model logic shown on the right. Patient entities begin their journey at the arrival point (source) on the left, and are then channeled either to normal (maternityA) or complicated (maternityB) delivery or observation services. The remainder of the patient pathway channels patients home or to a hospital unit, i) the maternity ward (S405) or ii) the patient hotel (NNBAR). The pathway is constrained by resources, the number of resources is stated in Table 1.

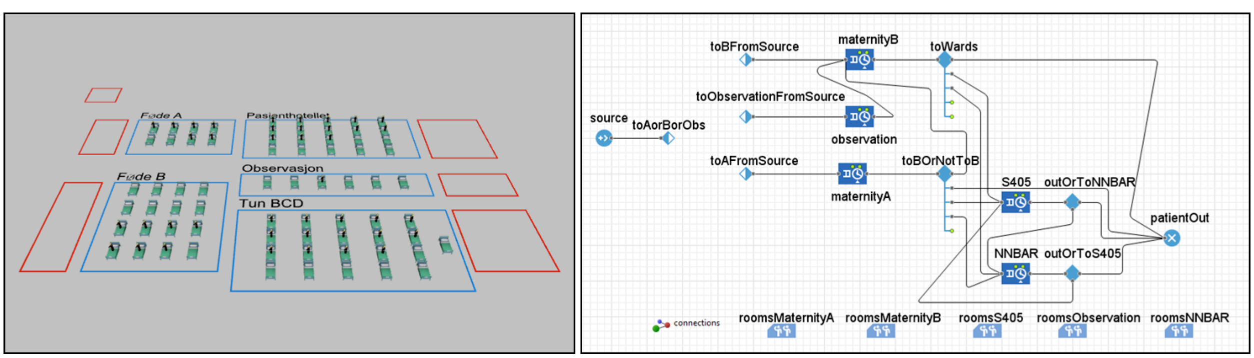

Figure 4: Obstetrics department DES model and the logic.

This DES model was produced quickly and was useful to address the questions specified during the problem structuring phase. However it was relatively inflexible, since the scope was constrained by the originally specification. Parametric and some structural changes could be investigated to a degree.

4.2 The Hybrid AB-DES Model

The second model was a loosely coupled AB-DES model, and has two modes: stochastic and deterministic. This model treats the patient as a more active agent. The patients interact with the same passive DES representation of the obstetrics department in both modes. The deterministic mode enables empirical data to drive the agents through the model (process durations and route through the department are known). In the stochastic mode, process durations and route choices are randomly sampled.

4.2.1 DES Part

The second DES developed, see the right hand side of Figure 5, consists of multiple simple DES models which are loosely coupled. This provided greater flexibility and scope to explore structural changes. The reason why there are multiple DES models is due to the accompanying visualizations of these components, see the left hand side of Figure 5 and note that it uses the same visualization as the DES only model. It is anticipated that the visual aspects of the model can be improved to allow for a single abstract model to represent all aspects of the department with the visualization decoupled from the model logic. Visualizations are important to assess the validity of the model with stakeholders.

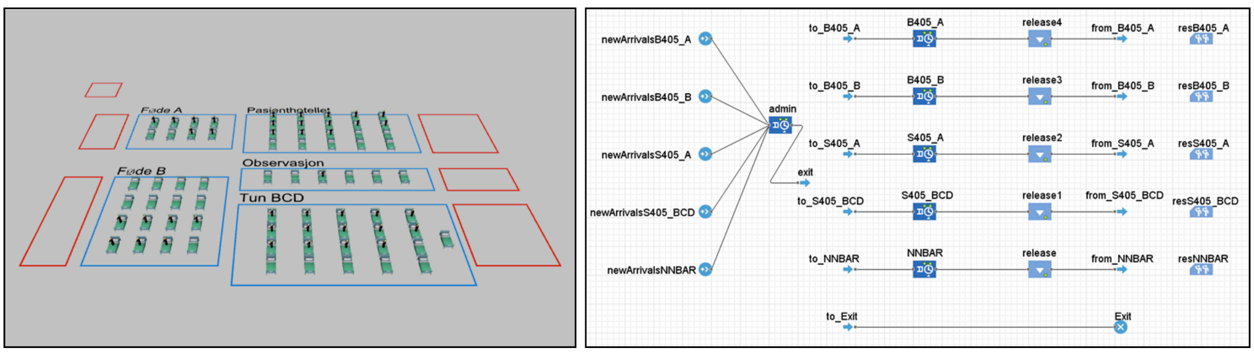

Figure 5: Obstetrics department AB-DES model and the logic.

This second DES model draws upon the approach developed for the hybrid modeling of the social and health care effects of age related macular degeneration (Viana et al. 2012), where the entity is replaced with an agent equivalent, an active patient, which contains the pathway rather than the pathway being contained with the DES model. The underlying DES model becomes a passive lattice-structure of nodes that the patient entities can attach to, based on their inner logic. The underlying structure is used to organize and limit ward resources, such as beds, and to assess utilization of these, identify bottlenecks, capture results, and to provide the visualization of the department.

4.2.2 ABM Part

The patient agent in the AB-DES is an active entity. Each patient entity contains demographic information, a patient pathway, and structure to collect information about the patient's visit. The AB-DES model transfers the pathway decisions from the department level DES, to the patient agent. The two pathway representations used in the AB-DES model are: 1) *Stochastic mode* a state chart patient pathway (see left side of Figure 6), which samples from probability distributions for process durations and the proceeding process, and 2) *Deterministic mode,* an empirical data driven pathway (see right side of Figure 6), which uses information extracted from hospital systems to recreate patient visit as they were recorded in the hospital systems (LoS at each process and route through the system is known). Importantly, since the movement of the patient entities was limited by the availability of resources (hospital beds) in the model, queuing not observed in the empirical data could occur, which would indicate a deviation between the modeled restrictions on resource allocation and real behavior, or problems with the empirical data.

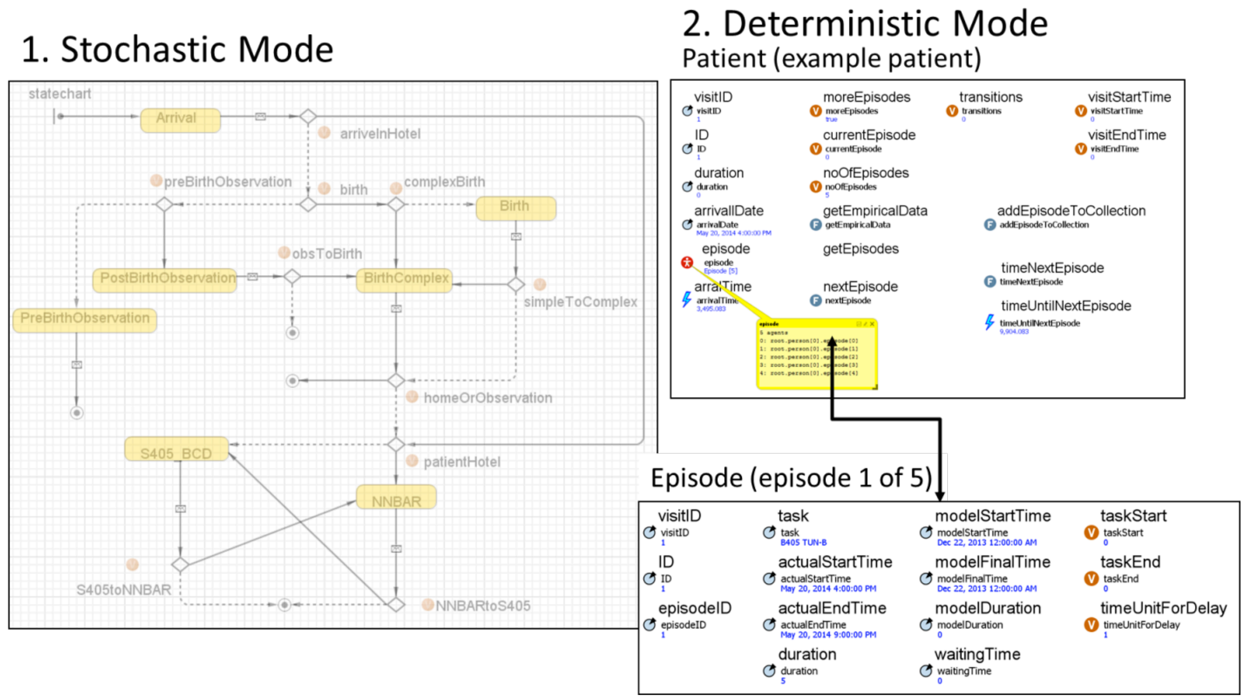

Figure 6: Patient agent embedded pathways 1) Stochastic state chart 2) Deterministic data driven.

The patient agents in this specific AB-DES model did not directly interact with other patient agents, only with the underlying DES structure. There are many ways that these patient agents could be developed. This is one reason why some consider simulation to be both an “art” and “science” due to these types of subjective decisions (Shannon 1998).

5 SCENARIOS

To evaluate the developed simulation models, three hypothetical scenarios are considered, see table 4. Are the developed models capable of evaluating the scenarios? How much effort is involved to achieve this? For this paper the scenarios and the results from the scenarios will not be used to inform decisions in the maternity unit, but to evaluate the functionality of the developed models.

Table 4: Scenarios.

Scenario	Description
1. Reference condition (Data driven)	Running the empirical data through the model, as a form of validation. Tests if the model can reproduce historical data, given known constraints.
2. Arrival patterns	Increasing the arrival rate by 25%. Expanding the catchment area
3. Changing pathways	Increase the probability of those with complicated births using the patient hotel rather than observation (50% more likely changing from 43.5% to 65.25%).

6 RESULTS

The models produce a lot of detailed results. Information can be obtained over time: the utilization of resources, the waiting time for wards, the LoS by ward in addition to arrival pattern information and number of episodes for validation purpose. For this paper, aggregate information collected over a year, relating to utilization of resources, total LoS, number of episodes per visit, and total number of arrivals to the department are considered. Table 5 provides the results generated by each model for each scenario. Apart from the AB-DES in deterministic mode, each model was run five times due to their stochastic nature. Scenario 1 results are used as a baseline to compare the other scenario results for this paper, as they should ideally replicate the historical data extracted from the system. Please note that the focus of this paper is on the technical aspects of the model rather than the policy impacts and the results should be considered as illustrative. While it may be technically possible to implement an equivalent of the deterministic mode in the DES model, this would be impractical in the extreme, and was therefore not attempted.

Table 5: Aggregated yearly results by model and scenario. 95% confidence intervals are provided in parentheses where available. Scenario 1 the data driven approach represents historical data.

Scenario	1. Reference condition						
	Data driven / deterministic mode	Stochastic mode					
	AB-DES*	DES			AB-DES		
Result	Mean	Mean	95% CI Lower	95% CI Upper	Mean	95% CI Lower	95% CI Upper
Number of patient visits	5.727	5,728	5,689	5,768	5,770	5,704	5,835
Length of stay (hours)	85.04	78.37	76.44	80.29	82.88	77.03	88.72
Number of episodes per visit	1.99	2.13	2.12	2.14	1.98	1.98	1.99
Normal delivery utilization (%)	31.24	32.68	31.08	34.29	29.79	28.47	31.11
Complicated delivery utilization (%)	46.29	47.63	46.49	48.77	43.44	41.62	45.25
Observation utilization (%)	65.79	69.11	62.66	75.55	63.71	61.40	66.02
Maternity utilization (%)	68.61	74.30	72.86	75.74	66.78	64.57	68.99
Patient hotel utilization (%)	86.19	88.00	86.75	89.26	84.71	83.50	85.91

*Raw data from the hospital records run throuth the model

Scenario	2. Arrival patterns						3. Changing pathways					
	DES			AB-DES			DES			AB-DES		
Result	Mean	95% CI Lower	95% CI Upper	Mean	95% CI Lower	95% CI Upper	Mean	95% CI Lower	95% CI Upper	Mean	95% CI Lower	95% CI Upper
Number of patient visits	6,784	6,682	6,887	6,684	6,570	6,798	5,653	5,525	5,781	5,722	5,591	5,853
Length of stay (hours)	253.50	135.66	371.35	315.15	225.27	405.04	103.71	50.69	156.73	82.88	69.81	95.94
Number of episodes per visit	2.11	2.10	2.12	1.98	1.97	2.00	2.10	2.09	2.11	1.98	1.97	2.00
Normal delivery utilization (%)	41.95	35.06	48.84	37.52	32.84	42.21	32.23	29.47	34.99	29.79	26.84	32.74
Complicated delivery utilization (%)	58.17	55.86	60.47	53.22	50.23	56.20	47.59	45.97	49.21	43.43	39.36	47.50
Observation utilization (%)	64.99	62.83	67.15	77.01	70.13	83.89	53.56	47.80	59.32	63.71	58.54	68.89
Maternity utilization (%)	99.19	98.63	99.75	98.14	96.38	99.90	57.65	54.76	60.54	66.78	61.84	71.71
Patient hotel utilization (%)	95.68	93.72	97.64	84.04	81.35	86.72	97.88	94.76	100.00	84.70	82.00	87.41

Differences between the statistical estimates of the raw data and the AB-DES model in deterministic mode are caused by queuing from limited resources in the model, which did not perfectly match the behavior of the department as represented in the medical records. The differences between the DES and the AB-DES results for scenarios 2 and 3 are attributable to the level of detailed control over the routing of patients through the department. More fine grained control was possible in the AB-DES as the patient agents, contained parameters about where to go next. It was more straightforward in the DES model to increase the arrival rate by 25% (scenario 1), as the DES model has a single source representing patient arrivals. In the AB-DES model there are different arrival points for different patient groups. This allows for different parameterization of each patient group, but as a consequence takes longer to parameterize. Increased arrivals as expected resulted in longer length of stay and also increased utilization in both models, except for the observation ward utilization in the DES model, this was due to how observation was handled in the DES model, with fewer patient being routed here because of the design of the model. Changing the pathway structure (scenario 2) resulted in dissimilar results between the DES and the AB-

DES model. This can be attributed to the coarser routing strategy in the DES model which related to all the mothers who enter the system rather than specific groups.

7 DISCUSSION

We discuss the model results briefly with respect to the scenarios. Scenario 2, the arrival pattern scenario, was very straightforward to implement in both the DES and the AB-DES model. Since the DES model had a single point of arrival, a single alteration was sufficient, while the AB-DES model required an increase in the number of arrivals in each group of agents representing different patient groups.

Scenario 3, the changing pathway scenario, was also easy to implement in both models. In the DES model we needed to change the routing out priority at two points, to represent the increase the routing probability to the patient hotel and reduce the routing probability to the maternity ward. In the AB-DES it was slightly easier we needed to change the probability of being routed to the patient hotel in a particular agent group (the complicated births group) the probability of being routed to the maternity ward is automatically calculated in this model as (1-probability of being routed to the hotel).

The key finding of this paper relates to scenario 1, the data driven scenario, which was implemented in the AB-DES model and not practically implemented in the DES model. The AB-DES model enabled the data to drive the patient through their visit. The ability to use empirical information to drive the AB-DES model was important to illustrate some potential issues with the episode data. Of the 12,119 episodes 235 had different model start times compared with historical data because resources were in use. This could indicate errors in the model, or that the department, when beyond the nominal capacity, finds practical solutions other than queuing the patients. These deviations can be important to identifying a proper representation of how the department in question actually behaves. Potential problems with the data are likely due to incorrect coding of patient location relating to an episode(s), which we are able to follow up. The model is used to validate the data. In order to be able to achieve the same ability in the passive entity DES we would have to program each activity with a list, as the patients are passive entities. This did not seem practically worthwhile, when being much easier to implement in the AB-DES model.

The level of experience of the modeler(s), having a clear scope, iteration, deciding when to stop, having an objective a clear breakpoint are all important factors when it comes to modeling. These are influenced by the modeling paradigms the modeler knows, if you are only taught methods in isolation you will only use them in isolation. Knowing the limitations of each paradigm, and understanding clearly how they work is important if you would like to combine them in any way. Yes you can use a single paradigm to model anything but as stated in the background and illustrated in this paper, it is less efficient. It takes longer and can require overly complicated structures and code. In fact we didn’t attempt to recode the DES model to enable it to be driven by the data, as we knew it would take a long time, likely be more complicated than we originally thought, and because we knew how to combine modeling techniques from different paradigms in a way suitable for our purpose.

8 CONCLUSION

This paper has attempted to illustrate certain benefits and drawbacks of using hybrid simulation. The models were developed to address a practical concern within a hospital environment. This paper focuses on the technical and philosophical modeling perspectives rather than the policy implications of the models findings. Two models were developed, a DES model and an AB-DES model. They were evaluated against three scenarios. The two hypothetical scenarios were relatively easy to implement in both models, with slightly more work required when adjusting the AB-DES model. However, the hybrid AB-DES model allows for more types of modifications than does the pure DES model. The process of running the empirical records through the model was only practically feasible using the AB-DES model, and this process revealed deviations between model performance and statistical estimates that could be crucial by identifying possible data error, or enabling a search for ways to improve the match between model and actual department behavior when encumbered beyond nominal capacity.

Specific areas for future work include: i) to explore the level of randomness within stochastic hybrid models using the JSIT library (Rossiter 2015), ii) to conduct a review of the existing hybrid modelling frameworks that have emerged in multiple domains (health, construction, software engineering etc.), to identify common structures, design patterns, archetypes and teaching methods, iv) to evaluate the impact hybrid modelling has on model validation and verification, such as visualizations and interaction with stakeholders, and finally, v) we have an ambition to perform data analysis, both pre and post model development/runs seamlessly with integrated R, or alternative specialized statistical tools.

We would like to improve the flexibility of the approach whilst balancing the accessibility and understandability of the models to non-modelers. By approach, we mean using the best methods to model different parts of the system, that are capable of dealing with changes, loosely coupled, and enable the data on which the model is based to be validated by the model.

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