A Review on Discrete-event Simulation and System Dynamics Studies for Healthcare Problems

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Keywords: System Dynamics, Discrete-event Simulation, Healthcare Systems, Modelling.

Abstract: Modeling is the major necessity to enhance the existing systems. Healthcare systems also need to model for advancing delivered services without compromising any other objectives. Thus, simulation techniques are frequently preferred in healthcare problems. As was to be expected, simulation has various applications which yields result in different perspectives. This study discusses two popular simulation techniques; discrete event simulation and system dynamics techniques in healthcare system applications. The applications are examined under four main branches based on their scopes. As a result, this paper evaluates which of these simulation techniques is more practical for different natured healthcare problems.

1 INTRODUCTION

In healthcare problems, main objective must be to manage overall system by considering patients, care givers and governmental regulations. In many applications, proposed models generally create a solution to currently known problem by altering a constraint or a parameter. However, this solution may generate a new problem or increase the impact of the existing one. Analyzing the influences of proposed solutions in real systems may be expensive, time consuming and inefficient for ongoing processes (Forsberg et al., 2011; Sterman, 2006). Thus, to overcome such problems, simulation models are preferred.

Simulation modeling has been a frequently used technique in healthcare for more than four decades (Brailsford, 2008). In simulation modeling, applied methods have large spectrum starting from behavioral to mathematical models (Jeffrey and Seaton, 1995; Fildes and Ranyard, 1997). Basically, modelers create solutions for patient flow and capacity planning.

Discrete event simulation (DES) is accepted as one of the most popular modeling techniques (Clark, 1999). Thus, DES applications on healthcare have a significant dominance compared to system dynamics (SD) method (Brailsford and Hilton, 2001). However, 70% of SD researches are done to solve real life problems, only the half of DES studies show the same performance (Jahangirian et al., 2010).

In this study, SD and DES modeling techniques are compared for specifically healthcare system problems. To be able to reach this goal, healthcare problems are decomposed based on their scopes into 4 major areas:

- Short-term resource management (SRM)
- Process improvement (PI)
- Forecasting & long-term strategy planning (FLSP)
- Causality (C)

In the following sections, DES and SD applications in healthcare will be discussed in detail under these four areas.

2 APPLICATIONS IN HEALTHCARE

Stochastic systems and queuing models could be interpreted as DES models with a preliminary condition. Under these circumstances, entities should be represented by discrete states over time (Ramwadhdoebe et al., 2009; Fialho et al., 2011). In this technique, modeler needs a clear event list of the system and input data must be collected. The data must be statistically appropriate. These requirements are generally seen as weaknesses of DES method. The strength of DES is the ability to incorporate system details, time dependent behavior, and system constraints. DES allows decision makers to access

Gönül-Sezer E. and Ocak Z..
A Review on Discrete-event Simulation and System Dynamics Studies for Healthcare Problems.
DOI: 10.5220/0005556302970302
In *Proceedings of the 5th International Conference on Simulation and Modeling Methodologies, Technologies and Applications* (SIMULTECH-2015), pages 297-302
ISBN: 978-989-758-120-5

information about system performance as well as insight through the effects of changing conditions over time (Jun et al., 1999; Griffin et al., 2012).

SD models are constructed by stock and flow variables using the feedback theory. Usage of stock and flow diagrams offers an advantage to understand and to clarify the system behavior over time. The representation of feedback system reflects the interactions among variables in overall system easily. Another advantage of SD is in data collection procedure. In SD, both quantitative and qualitative data could be used without any restriction which is not applicable in DES applications.

2.1 Short-term Resource Management (SRM)

Short-term planning in emergency rooms, clinics and operating theatres are frequently studied in DES due to discrete nature of these systems (Fone et al., 2003). In addition to this, some researchers claim that there is a significant difficulty to study complex or combination of multistage systems in DES (Günal and Pidd, 2010). This statement could be explained by the nature of the method; changing the scope of the model means new data is required but that also creates new restrictions in data analysis stage of DES. Thus, adding new data is challenging. Capacity management problems and patient flow issues in healthcare are more popular areas where DES is used. Critical resource and capacity problems in emergency rooms, catheterization rooms, clinics, and intensive care units are solved with this simulation technique (Ahmed and Alkhamis, 2009; Kadri et al., 2014; Rado et al., 2014). In addition to single-stage problems, some DES models are constituted for larger resource allocation problems. Šteins et al. (2010) develops a model for his thesis which aims to solve matter of resource utilization for a combination of operating room, intensive care and radiology examination units. Meanwhile overall hospital resource allocation problems are also solved by DES approach, but they are generally hybrid models, and such studies are shown rarely in literature (Cochran and Bharti, 2006).

Geranmayeh and Iyer (2008) analyze the capacity planning for critical resources such as critical services and procedures, required equipment in an emergency department by using SD. They try to develop an economic justification for investment on laboratory and diagnostic facilities, and physicians. Wu et al. (2013) try to portrait differentiating pediatric workforce as a reaction to altering demand on this specific sector in Taiwan. The study proposes projections for short-term demand and supply changes. As shown in given examples, SD models are used for resource management problems. However, nature of method encourages the modelers to make further analysis on long-term resource and capacity management problems.

2.2 Process Improvement (PI)

In healthcare systems, the major concern of process improvement problems is patient flow issues and schedules. DES applications on patient flow problems show that the main objective of modelers is eliminating queues in specific departments. Some of these papers only focus on enhancing operating rooms schedules and reducing delay times for examination and other operations (Marjamaa et al., 2009; Denton et al., 2010). Additionally, alternatives for interacting departments are also investigated (Kuhl, 2012). Such models become too complex, when a hospital or an institution is taken into consideration as whole. DES applications are more suitable for compact process improvement problems.

In process improvement analysis, diminishing waiting times of patients in any unit of hospitals is one of the most popular purposes in healthcare. Minimizing the delays means eliminating bottlenecks in patient flow processes.

A feedback system is utilized for an accident and emergency department constituting a dynamic model for variation of schedule (delay or lead time) in accident and emergency departments in United Kingdom (Lane et al., 2000). To diminish waiting time of patients, they propose to increase the level of some critical resources and reduce bed capacity. In another study, as a preliminary model, waiting list model in cardiac surgery is developed using SD technique (Hilton, 2001). The main objective of this study was to understand dynamics of waiting list by using influence diagrams and interactions among resources, schedules, etc. Also in another study, the emergency and urgent care system is modeled by system dynamics based on patient flow pathways, and process improvement strategies are examined for five different scenarios (Lattimer et al., 2004).

2.3 Forecasting and Long-term Strategy Planning (FLSP)

Discrete event simulation technique is utilized for long-term strategy planning in healthcare as hybrid studies only. While DES solves the problems in policy implementations, SD models are appropriate for policy design interventions (Zulkepli et al., 2012). Therefore, SD is employed in forecasting stage and to model the operation (based on the forecasts) DES is applied in such studies.

To predict demand on long-term care in Hampshire, a combined model has been developed (Brailsford et al., 2010). In the first part, SD is used to estimate population and dynamic demographic changes in the land for upcoming 20 years. Then, a DES model is constructed for resource and labor utilization problems based on handled scenarios from SD part of the study. In another study, the UK healthcare system is analyzed for different governance designs. The impacts and consequences of designs on organizations are modeled as a hybrid DES and SD model (Chahal et al., 2008). This means that, in forecasting, DES is not capable. Therefore, to provide estimation for future, modelers need SD in simulation modeling. After creating forecasts using SD model, DES is applicable to animate the scenario. The impacts of tactical level results created in SD model are analyzed in operational level using DES technique.

Under this section, SD modelers basically examine the role and interaction of risk factors and develop forecasts based on their behavior. Townshend and Turner (2002) studied a sexually transmitted infection caused by bacteria of the genus Chlamydia. The model reflects the future effects of bacteria on behavior of infertility in the UK. In this study, they provide forecasts for number of the people who will be infected and forecast for people treated. Same year, another model developed for one of the critical communicable diseases; AIDS. This model predicts the prevalence and volume of this particular epidemic in Austria (Rauner, 2002). In another study, a model was proposed for chronic disease prevention and get projections for this disease for 50 simulated years by using population health and healthcare delivery system causal loop diagrams (Homer et al., 2004). Chen (2003) handled the non-acute care, home-based health services for elders, and builds a dynamic model on patient actions as a supplementary study to plan longitudinal budget and capacity strategies in Norway. Barber and his colleague (2010) also chose SD modeling approach to estimate the medical specialist demand in Spain, for year 2025. Another study tried to estimate a next five-year -population for ambulatory health demands in the US which can be used by strategic planners (Diaz et al., 2012). Merrill et al. (2013) stated the policies to execute electronic health information exchange reports for a regional health information department. Then, some policies are advised to overcome the gap between resulted demand and supply. Again, Ansah et al. (2014) made projections for future demand analysis in healthcare. The study shows rising demand on long-term care for elder people and emphasize on strategic thinking on resources such as personnel, equipment, etc.

2.4 Causality (C)

In DES, identifying the relationship among variables is challenging because it has state variables which indicates events, queues, resources and time (Dong et al., 2012). To overcome this problem, again hybrid models are preferred in literature (Mittal, 2013; Guizzardi et al., 2012). DES models could interpret the relation between sequential events individually. By using this characteristic of DES, a model is built for breast cancer and its screening procedures (Brailsford, 2012). Including the patients' behavioral characteristics and other psychological data in the model as attributes of entities is the most attractive side of the study. Brailsford (2014) suggests hybrid models to add more behavioral causes in simulation models. Also another hybrid model utilized to investigate interventions for colon cancer screening. SD determines how factors affect the screening rate. Afterwards, six different interventions are examined for screening levels on DES (Hosking et al., 2013).

Lubyansky (2005) created an SD model to analyze the surgery system response in the US in case of peak periods. These periods are explained with sudden increases in demand on healthcare services. Main goal was to model effects on surge capacity based on demands of patients, supplied resources (staff, equipment, material, operation place, etc.), and healthcare policies in the US. Faezipour and Ferreira (2011) studied the factors affecting the patient satisfaction in healthcare and develop an SD model to illustrate the relationship among these factors. By this way, they developed a plan for a more sustainable healthcare system. Causal hypothesis employed in SD are also utilized for Switzerland Health Reform. The service quality and costs are analyzed by thinking population aging, inflation, insurance and poverty (Hirsch et al., 2012).

Another model was developed to understand the dynamics of long-term care laws, culture and facilities in Taiwan are illustrated by seeking patient satisfaction, service quality, administrative skills, medical care personnel and resources Hsiao and Huang, 2012). The factors related with global attention to healthcare systems are analyzed with another SD model that concerns about the behavioral impacts of financing, national priority and differences in health policy approaches (Hafner and Shiffman, 2013). Another study is constituted for interpreting the dynamics of child mortality in Uganda (Rwashana et al., 2014). The factors related with neonatal mortality are examined using causal loops. The discrepancy in resources and lack of awareness on health issues are determined to be as the most critical factors in this study.

3 COMPARISON

The comparisons between DES and SD are developed by using two different perspectives. As a general comparison, the basic steps of modeling are used. At the second one, the listed scopes of healthcare problems in introduction are evaluated by considering the first comparison method.

Table 1: Comparison of DES and SD based on simulation steps.

	DES	SD
Scope	Operational	Strategic
Design the model	Strict event lists based on queuing model	Influence diagrams based on variables in model
Gather the data	Statistically approved data	No restriction on data
Validate the model	t-test	Structural and behavioral checks
Improve the system	Statistically approved alternative models	Strategy development based on policy analysis

Reconsidering the healthcare problems based on the five modeling steps for four major healthcare problem areas on DES and SD applications in literature, a ranking can be conducted as seen in Table 2.

Table 2: Applicability of simulation types to healthcare problems.

	Healthcare Applications			
	(SRM)	**(PI)**	**(FLSP)**	**(C)**
DES	Strong	Strong	Moderate	Weak
SD	Weak	Moderate	Strong	Strong

4 CONCLUSION AND FUTURE WORK

Tailoring multilevel healthcare problems by DES is generally problematic. Therefore, DES is preferred for short-term decisions and analysis on specific processes. As a result, short-term problems in patient flow and resource allocation problems are modeled using this technique. If the modeler needs to understand causes of a phenomena or wants to get long-term consequences of his decisions, SD could be a better choice. Thus, forecasting, causal relations and long-term consequences of actions could be represented better with this technique. Considering the strong aspects of both methods, hybrid studies that combine these two methods are currently in demand.

This study provides many suggestions for future research . The study can be applied to generate multiple comparisons for different agent-based simulation techniques. Also, this study can be extended with numerical and/or statistical evidences and results.

Future research should examine the interrelated problems of how to process the available information on these simulation techniques and how to use these measures to best control the system.

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