Proceedings of the 2016 Winter Simulation Conference
T. M. K. Roeder, P. I. Frazier, R. Szechtman, E. Zhou, T. Huschka, and S. E. Chick, eds.

MODELING OF HEALTHCARE SYSTEMS: PAST, CURRENT AND FUTURE TRENDS

Amr Arisha
Wael Rashwan

3S Group, College of Business,
Dublin Institute of Technology (DIT),
DUBLIN 2, IRELAND

ABSTRACT

Increasing demand for healthcare services, due to changes in demographic shifts and constraints in healthcare funding, make it harder to manage effective, sustainable healthcare systems. Many healthcare modeling exercises have been undertaken with the aim of supporting the decision-making process. This paper reviews all of the 456 articles published by the Winter Simulation Conference over the past 48 years (1967–2015) on the subject of modeling and healthcare system simulation, and analyzes the relative frequency of approaches used. A multi-dimensional taxonomy is applied to encompass the modeling techniques, problem applications and decision levels reported in the articles. One of the most significant changes in the modeling of healthcare systems is the fact that Discrete-event Simulation (DES) is no longer used as an autonomous method, but rather as an integral part of the solution. The mixed-methods, hybrid and multi-paradigm approaches feature strongly in the current direction of modeling in healthcare systems.

1 INTRODUCTION

Health systems can be described as complex systems characterized by a high level of uncertainty and dynamism (Rashwan et al. 2013), as well as much variability (Brailsford 2007). Variability exists in all systems and can have an enormous impact on productivity and performance. In the healthcare context, variability results from factors within our control (such as staff training, checklist, room temperature) and beyond our immediate control (such as unscheduled patients, treatment time under complex conditions). Variability can be disruptive in any system, to various degrees. Therefore, the need for techniques and sophisticated tools that make it possible to measure, understand and manage variability will always top the wish-list of management teams.

Operations Research (OR) has contributed strongly to understanding the different levels of complexity of healthcare processes, including the variability and uncertainty of activities. Over the past 50 years, OR researchers have worked closely with professions in the management of the healthcare system, seeking to offer a diverse portfolio of solutions to address the current issues at different decision levels. Modeling the unit, process or system has always been the first phase of most of the studies, regardless of the algorithm or framework applied as a solution.

One of the important factors to ensure a good model is the quality of the data phase. The modeling outcome is dependent on the data from different levels (Figure 1), particularly when the simulation constitutes the ultimate environment for experiments. Every data level can provide insights that can be used to understand the system. For example, level 0 data identifies a portion of the real-world system that will be modeled. As the level is higher, the measurement and observations make more sense. Level 3 consists of the structured data, which, along with the modular data, is used for the modeling. The complexity of the system depends on the availability and accuracy of the data levels (Zeigler, Praehofer, and Kim 2000). The modeling of healthcare systems often suffers from a dearth of data, especially at level 0 and 1.

Several review papers have been published over the years on healthcare modeling and simulation. Jun, Jacobson, and Swisher (1999) reviewed the modeling of healthcare systems, with an emphasis on Discrete-event Simulation, while Fone et al. (2003) conducted a systematic review of the use of simulation modeling in population health. Fakhimi and Mustafee (2012) focused on UK healthcare modeling. A comprehensive review, which examined 342 articles based on nine criteria, was conducted by (Brailsford et al. 2009). Their review describes a multi-dimensional method for classifying the literature on simulation and modeling in the healthcare context. This paper reviews the publications of the Proceedings of the Winter Simulation Conferences (WSC) (1967–2015).

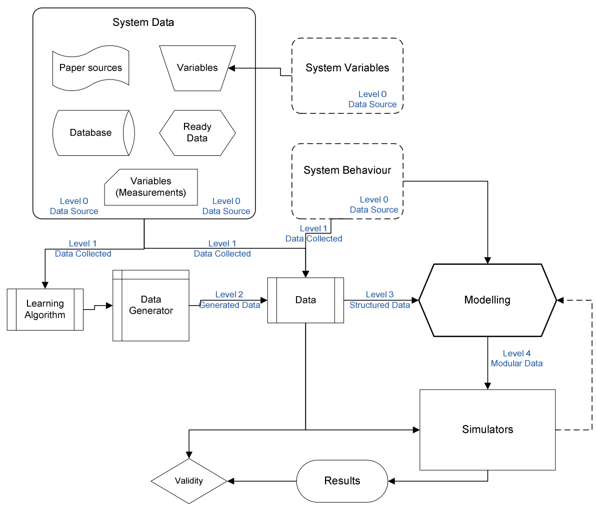


Figure 1: Data levels for modeling.

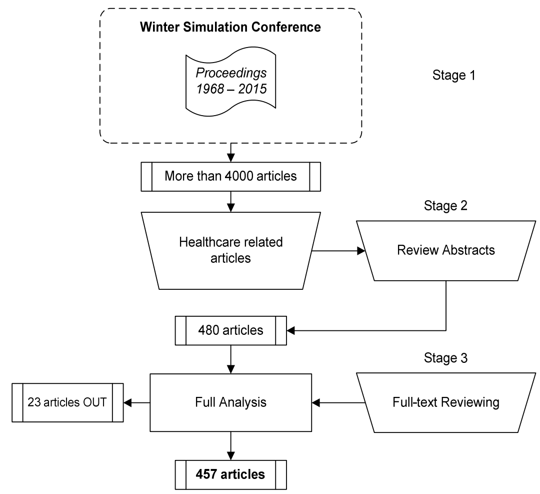


Figure 2: Stages of the review process.

2 REVIEW METHODOLOGY

This study focuses on reviewing WSC publications, but also looks at selected journal articles that are considered as landmarks in the field of healthcare modeling. The review took place in three successive stages (Figure 2). The first stage consisted of the scanning of over 4,000 articles to segregate the articles addressing healthcare applications. Interestingly, not all the healthcare-related papers were assigned to the healthcare track in WSC. Therefore, a full review of every article published in the WSC proceedings had to be completed. In the second stage, 480 articles were selected and 23 of these excluded, giving a total of 456 articles. In the third stage, abstracts were reviewed and a full-text review of the 456 articles was completed.

The papers selected were extensively analyzed based on the year of publishing, method employed, country of the study, level of the study, performance indicators applied, and the problem application. For each of the criteria, more categories or criteria were included to enhance the analysis. For example, ‘application problem’ was classified into six main subgroups (Figure 3).

Similarly, articles were separated based on the ‘performance indicators’ used in the study. The main measures applied were cost measures and cost-effectiveness, length of stay (LoS), occupancy level, quality-adjusted life year (QALY), resource use, response time, throughput time, and waiting time. The analysis considered the country of the study and the impact of the decision level of the study (i.e. clinic, GP, hospital, unit/laboratory, multiple units, national, regional). Few studies can focus on one or more decision levels subject to the application of the model. Many methods and approaches were reported in the literature, but could be categorized into three sets: single methods, mixed methods and hybrid methods. The single methods represent modeling applying Discrete-event Simulation (DES), System Dynamic (SD), Agent-Based (AB), Monte Carlo (MC), and others (i.e. mathematical models). Since simulation modeling is seldom used without statistical analysis, integrating statistical techniques into the models does not categorize them as mixed or hybrid models.

'Mixed methods' in this article refers to the use of the simulation modeling approach (i.e. MC, DES, SD, or AB) with another optimization or probabilistic technique (fuzzy logic, meta-modeling, AHP, etc.). The term 'hybrid methods' is defined as the use of two or more simulation modeling techniques (i.e. DES, SD, AB) in one model (Mustafee et al. 2015).

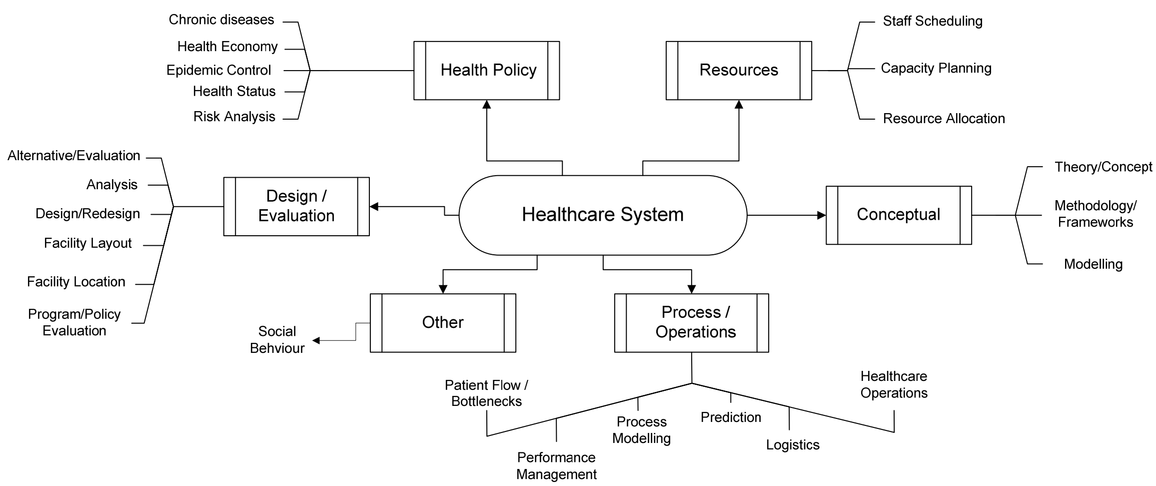


Figure 3: Healthcare system applications.

3 RESULTS

WSC publications in the area of modeling healthcare systems have much increased in recent years. System complexity challenges decision-makers to evaluate interventions that can improve the effectiveness and efficiency of healthcare delivery, and modeling (especially dynamic modeling) seems to leverage the data analytics growth (Marshall et al. 2015).

In terms of the country focused on in the research articles, most of the publications come from the USA (57% of the articles), UK (16%) and Canada (5%), while South Korea, Spain, Germany, Ireland, France, Netherland and Japan account for 22% of the total of published papers. Most of the problem applications have addressed operational and health policy issues, with less attention given to resources and the design evaluation of new systems (Figure 4). Each of the 456 articles was also classified according to the key performance indicators (KPIs) used in the model developed (Figure 5). As expected, most of the models primarily use patients' waiting/throughput time (32%) and cost indicators (26%). Length of stay (LoS) is another preferred indicator, used in 20% of the articles, followed by use of resources (15%). Discrete-event Simulation – as expected – was found to be the dominant modeling approach (65%) used in the papers reviewed, followed by mixed methods (11%) (Figure 6). In the past eight years, there has been growing interest in AB, SD and the hybrid methods.

3.1 Mixed Methods

Mixing methods can compensate for the weaknesses and drawbacks of a single method (Brailsford 2015). Numerous studies presented during WSC proceedings have attempted to combine simulation methods with other methods. Over the period (1972–2015), 50 articles (11%) combined simulation methods with other techniques. Most of them (70%) mix simulation and optimization, while the remaining combines simulation with a probabilistic model. DES is the preferred simulation approach in 36 papers, while 14 studies used ABS (n=9), MC (n=4) and SD (n=1). WSC mixed-methods publications have tripled in the past six years (Figure 7 and Figure 8). Interestingly, the spread of the modeling using different application areas proves the growth in attention to this method (Figure 8).

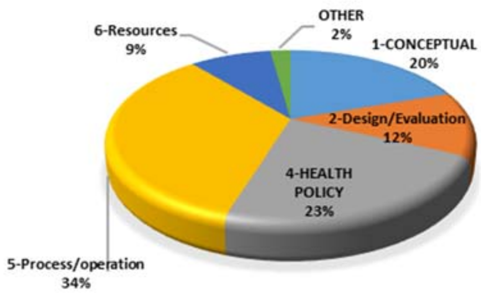


Figure 4: Analysis of articles by applications.

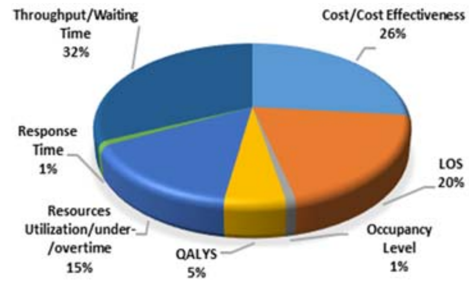


Figure 5: Analysis of articles by performance.

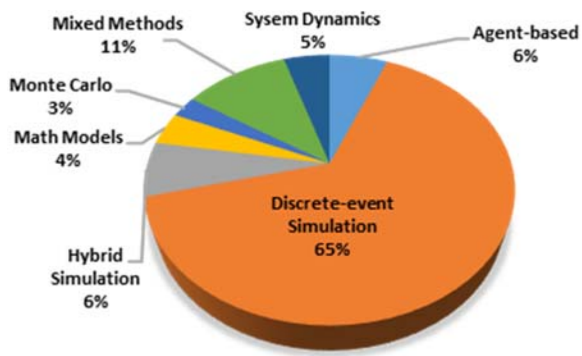
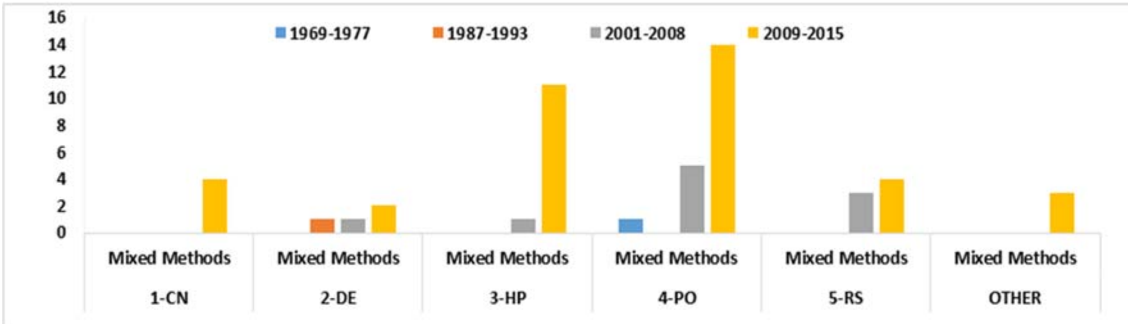


Figure 6: Analysis of articles by modeling approach.

Figure 7: Mixed-methods articles in relation to decision levels.

3.1.1 System Dynamics and Other Methods

Ferranti and Freitas Filho (2011) proposed a dynamic fuzzy simulation model that integrates the system dynamics method and fuzzy modeling to explore the processes of human ageing. The model simulates the occurrence of risk events from birth to death, combined with the representation of recovery processes. The model demonstrates how to generate mortality curves from a population with specific characteristics, such as obesity and hypertension, and to test different interventions to reduce the mortality caused by a specific disease.



Note: CN= Conceptual; DE= Design/Evaluation; HP= Health Policy; PO= Process/Operation; RS= Resources; OT= Others.

Figure 8: Mixed-methods articles in relation to application areas.

3.1.2 Agent-Based and Other Methods

Nine models were found that combine Agent-based Simulation (ABS) with optimization and/or probabilistic methods. Six of them addressed epidemics and disease-related issues at the regional/community and unit levels, while the other three examined subjects such as optimizing ED performance and modeling social behavior. Use of ABS enables the analysis of particular individual behaviors and their interactions at the microscopic level, as well as flexible modeling of disease progression, the effects of provider interventions, and provider behavior models (Kasaie et al. 2010).

In the epidemiological studies, Dibble (2010) proposed using a genetic algorithm (GA) and ABS to optimize the deployment of scarce resources and disruptive interventions for controlling pandemic influenza. The ABS modeled the diffusion of pandemic influenza. The paper argues that real-time situation updates can significantly enhance the strategic usefulness of simulation. Kasaie et al. (2010) applied the Response Surface method to optimize resource allocation; the epidemic spreads and population dynamics were modeled using ABS. Similarly, Ozaltin, Dalgic, and Erenay (2014) used ABS to model the spread and transmission rates of influenza and a black-box optimization to optimize the age-specific vaccine distribution strategy to minimize the overall cost of the outbreak. ABS and cluster analysis were applied to estimate the proportion of recent tuberculosis transmission and explore the role of various factors in the epidemic system and sampling strategy (Kasaie, Dowdy, and Kelton 2014).

The ABS model for ED was also developed to help management to optimize ED performance (Cabrera et al. 2012). The model was combined with exhaustive search optimization to find the optimal staff configuration using the Monte Carlo method. Balaban (2014) addressed the return-to-work behavior of people with disabilities by applying ABS and Bayesian network methods.

3.1.3 Discrete-Event Simulation and Other Methods

Almost 30% of the articles referred to in this section used a combination of DES and probabilistic models; for example, DES and the semi-Markov Decision Process (MDP) to model and predict the patient enrolment process (McGarvey et al. 2007), while Vila-Parrish et al. (2008) modeled the inventory and ordering policies for perishable drugs in the setting of a hospital inpatient pharmacy for two stages of inventory, using DES and MDP. Hosseini and Taaffe (2014) merged the MDP and DES models for optimal scheduling of elective and non-elective surgeries. A hospital-wide simulation to model a multi-server, time-varying queuing network was reported by (Asli Ozen et al. 2014), aimed at enabling timely access to inpatient beds. The authors focused on the discharge profiles to mitigate the pressure on the inpatient beds. The main conclusions were that prioritized discharges have the biggest impact on reducing queue size.

Most of the publications integrated the DES and optimization methods (70%), by far the favorite method to study healthcare issues at different decision levels, but mostly at the unit level.

3.2 Hybrid Simulation Models

Modelers are often challenged to model the complex systems in totality. The claim is that this will provide coherent insights into the system. Lynch et al. (2015) used the simulation modeling paradigm to identify different levels of granularity so as to answer a specific set of questions. Developing large and complex healthcare models entails various ways of thinking to incorporate multiple stakeholders, policies, different types of patients and other complex elements (Zulkepli and Eldabi 2015). Hybrid approaches are becoming more popular because of the limitations of a single-approach paradigm (Viana 2014); more than 25 studies in the past six years have reported on the benefits of the hybrid modeling approach (Figure 9), especially for decisions at the regional/community level for problems such as epidemics and chronic diseases. Hybrid modeling was also used at the unit level (ED and ICU). Twelve studies of hybrid modeling provide a methodological and conceptual framework (Figure 10). This trend can be explained by the fact that hybrid simulation is an emerging topic that requires clarification regarding definition, use, integration, challenges, etc.

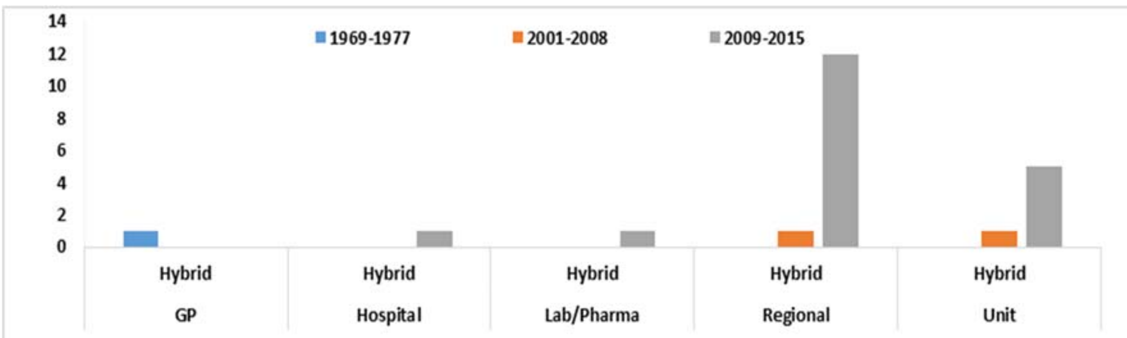
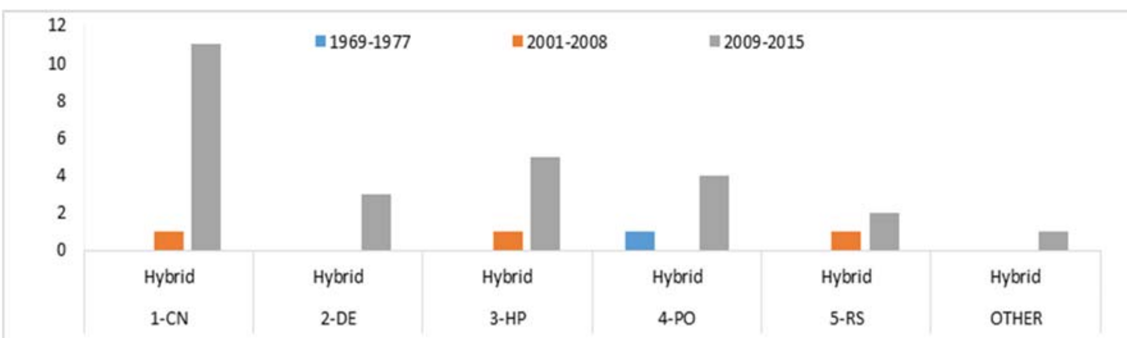


Figure 9: Hybrid simulation papers in relation to decision levels.



Note: **CN**= Conceptual; **DE**= Design/Evaluation; **HP**= Health Policy; **PO**= Process/Operation; **RS**= Resources; **OT**= Others.

Figure 10: Hybrid simulation papers in relation to application areas.

3.2.1 Hybrid Methods: Discrete and Continuous Simulation

In 1977, Standridge et al. proposed one of the earliest attempts to combine discrete and continuous simulation concerning primary healthcare in Indiana. The purpose of the model is long-term projection of the supply of and demand for primary care, and it is used to evaluate the need for additional staff supply. Hybrid DES and SD has gained momentum since SD modeling provides a holistic view while DES permits looking at the details (Brailsford 2008). Giachetti et al. (2005) discuss the results of a hybrid system developed to model patient appointment scheduling for an outpatient clinic. DES was used to analyze and make recommendations for improving patient cycle time, and SD was used to understand the factors leading to a high no-show rate. Chahal and Eldabi (2008) proposed the integration of DES and SD in modeling healthcare systems in the UK. The authors argued that hybrid simulation would aid in forming a synergy between strategic and operational management, since, in a system such as healthcare where both detailed and dynamic complexities are critical, decision-making process requires tools for comprehending such complexities. Zulkepli, Eldabi, and Mustafee (2012) proposed the DES-SD approach to model an integrated care system. These studies were extended by (Zulkepli and Eldabi 2015); the authors developed a guiding framework to consider when building a hybrid model. The framework is three-phased and is based on model decomposition into modules. The framework then assigns methods to these modules and identifies the communication strategies between them. The paper focuses on SD and DES. It also aims to allow modelers to consider key issues before starting the hybridization process, and it was tested to develop the model described in the previous paper (Zulkepli, Eldabi, and Mustafee 2012). Fakhimi, Mustafee, and Stergioulas (2015) presented a hybrid framework that integrates discrete and continuous simulation to develop more reliable models that neither ignore sustainable development dimensions nor mislead decision-makers into making decisions that ignore productivity and efficiency measures.

3.2.2 Hybrid Methods: Two Discrete Simulation Methods

A combination of DES and ABS with game theory was used by (Hagtvedt et al. 2009) to reduce ambulance diversion and examine the potential of proposed cooperative strategies. Anagnostou, Nouman, and Taylor (2013) also used ABS to simulate ambulance services, and DES to model an ED in London. Distributed simulation techniques link the two parts. Other applications of hybrid DES-ABS include modeling patient flow in a pre-operative hospital, incorporating nurse behavior (Pearce et al. 2010), and using DES and MC to investigate bed blocking in a cardiac ICU unit (Mustafee et al. 2012); MC was used to experiment with a different number of beds to examine bed management policies so as to mitigate bed blockage.

3.2.3 Hybrid Methods: More Than Two Methods

In 2011, Heath et al assembled a discussion panel representing a variety of perspectives on the topic of a hybrid method to use the simulation approaches ABS, SD and DES (Heath et al. 2011). They concluded that, despite the progress made in simulation hybridization, a pragmatic modeling methodology and toolkit for developing complete hybrid models was still not well developed. One of the issues raised was how to implement hybrid models considering the problems associated with the two different time-advance mechanisms. (Lynch et al. 2015) introduced a methodology to ease the generation of interoperable simulations; this was a major driver for developing the multi-paradigm modeling framework of ABS, DES and SD to represent interactions between elements at different granularity levels (macro, mesa and micro). Three components that a modeler needs to define when building a hybrid simulation model are the modules, module interfaces and updating rules (Onggo 2014). Brailsford (2015) argued that the increasing popularity of AnyLogic and the launch of other commercial software packages were evidence of the growing demand for hybrid modeling.

In healthcare technology evaluation, (Djanatliev and German 2013) proposed a multi-paradigm simulation mechanism to evaluate health technology innovations prospectively. This extends a previously presented hybrid approach using process-oriented DES for hospital modeling and generates agents dynamically from SD models.

A hybrid model is proposed by (Gao et al. 2015) to examine the health and cost impacts and intervention tradeoffs between different intervention strategies for diabetes. The hybrid structure of the model has two types of hybrid relationships: a producer-consumer (upstream-downstream) relationship between SD and ABS components, and, by contrast, ABS and DES elements that operate concurrently for a given individual.

4 DISCUSSION

The review of the 456 WSC publications provides insights into the application of modeling in healthcare systems. This paper has cited exemplars from WSC publications but it is acknowledged that extensive research efforts have been covered in publications by other sources that provide a significant contribution to this important field of knowledge.

WSC publications focusing on the use of modeling approaches for healthcare systems have steadily increased, from three articles in the 1960s, four to five in the 1970s and 80s, and around 10 in the 1990s and early 2000s to more than forty in the 2014 and 2015 WSC proceedings. This growth can be attributed to:

- the increasing demand for innovative solutions,
- the rapid increase in computational power (hardware),
- advances in information technology and simulation software,
- knowledge developed in system thinking and optimization, and
- changes in organizational culture.

From the review of the articles, it is evident that Discrete-event Simulation (DES) has been widely used in modeling systems and has dominated the WSC publications for many years. Simple frequency analysis shows that the number of DES papers has increased markedly since 2006. Among the 456 articles reviewed, at least 356 have DES either as a stand-alone model (296) or as part of a hybrid with another simulation approach such as SD or AB (Figure **11**). Even with the advances in simulation software and modeling approaches, there is still a focus on decisions at the unit level (Figure **12**). It is believed that this is because of the easier data accessibility at that level and, equally, the complexity of the interactions between system components. However, there is growing interest in using SD and AB models for regional and national decision levels, while the number of publications on the hybrid and mixed methods has increased, especially in the period 2009 to 2015.

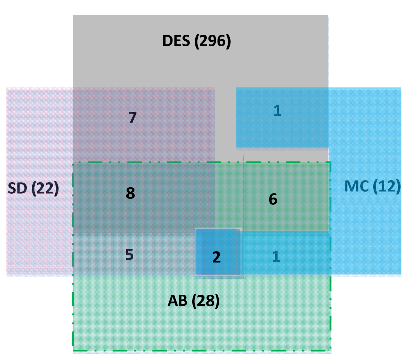


Figure 11: Modeling approaches.

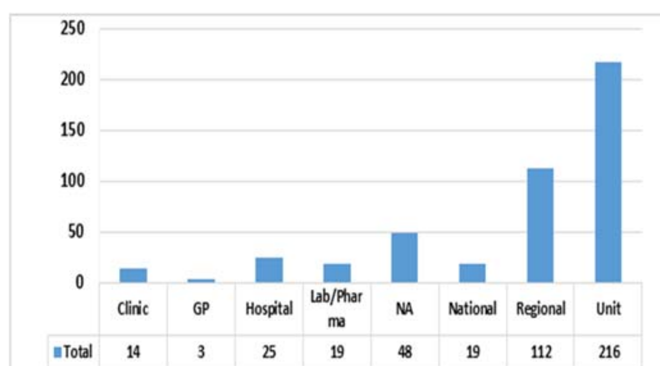


Figure 12: Decision Levels.

Most of the studies (77%) seem to have used total procedure time (TPT), length of stay (LoS) and cost measures as the key KPIs. They reported that these KPIs had been agreed with the management of the healthcare organizations. The focus is also on operational and process challenges (35%) and health policies (22%), with less attention to resources and design issues. This may be related to DES applications and capabilities in modeling operations and processes. However, with the growth in hardware and software technologies, DES is now seen to be able to model larger-scale systems (i.e. hospital or regional) (Boucherie, Hans, and Hartmann 2012).

There are limited studies that reported on the implementation of the models (Eldabi 2009). It is important to describe the implementation process as this helps the professionals to engage in the modeling projects and also promote the solution approach. Other benefits can also be gained from the procedure and methodology of working closely with decision-makers, who often gain new insights by carrying on the exercise of conceptual modeling. Whether the implementation fails or succeeds, reporting the experience of implementation is as critical for researchers as the key findings of the project. No matter how complex the modeled system is or what approaches are used, future modelers will continue facing implementation difficulties (Jun, Jacobson, and Swisher 1999)

5 CONCLUSION

The dynamic nature of contemporary healthcare settings requires the use of modeling approaches to understand the complexity of the health systems that, in turn, necessitates the acquisition of a proper level of data and knowledge. Examination of the 456 articles – published in the Winter Simulation Conference Proceedings over the past 48 years – shows that the modeling approaches have been through different phases of development. The proliferation in publications and growth in interest present unequivocal evidence that the use of modeling approaches, if successfully applied, significantly improves decisions related to healthcare management at various levels. Most of these papers are still using Discrete-event Simulation in modeling healthcare systems, with particular focus on a specific unit or department. Combining DES or dynamic modeling approaches with other analytical techniques (mixed methods) has matured over the past decade. The introduction of hybrid models in healthcare modeling is also another potential trend. Research in modeling healthcare systems, therefore, illustrates that dynamic and simulation models, if integrated appropriately, can be used in healthcare settings as an active decision-support system for the management team. Without compromising patient safety, managers can practice decision-making in certain clinical situations and develop reasoning for new strategies.

The future of modeling in healthcare systems is unclear. Data science has undergone a series of technological leaps. The massive growth in hardware and software will see modeling approaches changing to cope with increased computational power and new opportunities. This may lead management to engage in further system analysis, with the objective of fostering new capabilities. Modeling human behavior in a healthcare environment is another complex theme that has received significant attention in the modeling space during the past 12 years. As a result, the management of healthcare organizations has more awareness of the impact of staff burnout and motivation on productivity and the quality of services.

REFERENCES

Anagnostou, A, A. Nouman, and S. J. E. Taylor. 2013. “Distributed Hybrid Agent-Based Discrete Event Emergency Medical Services Simulation.” In *Proceedings of the 2013 Winter Simulation Conference*, edited by R. Pasupathy, S.-H. Kim, A. Tolk, R. Hill, and M. E. Kuhl, 1625–1636. Piscataway, New Jersey: Institute of Electrical and Electronics Engineers, Inc.

Ozen, A., H. Balasubramanian, P. Samra, M. Ehresman, H. Li, T. Fairman, and J. Roche. 2014. “The Impact Of Hourly Discharge Rates and Prioritization on Timely Access to Inpatient Beds.” In *Proceedings of the 2014 Winter Simulation Conference*, edited by A. Tolk, S. Y. Diallo, I. O. Ryzhov, L. Yilmaz, S. Buckley, and J. A. Miller, 956–963. Piscataway, New Jersey: Institute of Electrical and Electronics Engineers, Inc.

Balaban, M. 2014. “Return to Work Behavior of People with Disabilities: a Multi-Method Approach.” In *Proceedings of the 2014 Winter Simulation Conference*, edited by A. Tolk, S. Y. Diallo, I. O. Ryzhov, L. Yilmaz, S. Buckley, and J. A. Miller, 1561–1572. Piscataway, New Jersey: Institute of Electrical and Electronics Engineers, Inc.

Boucherie, R. J., E. W. Hans, and T. Hartmann. 2012. “Health Care Logistics and Space: Accounting For

The Physical Build Environment." In *Proceedings of the 2012 Winter Simulation Conference*, edited by C. Laroque, J. Himmelspach, R. Pasupathy, O. Rose, and A. M. Uhrmacher, 696–703. Piscataway, New Jersey: Institute of Electrical and Electronics Engineers, Inc.

Brailsford, S. 2007. "Tutorial: Advances and Challenges in Healthcare Simulation Modeling." In *Proceedings of the 2007 Winter Simulation Conference*, edited by S. G. Henderson, B. Biller, M.-H. Hsieh, J. Shortle, J. D. Tew, and R. R. Barton, 1436–1448. Piscataway, New Jersey: Institute of Electrical and Electronics Engineers, Inc.

Brailsford, S. 2008. "System Dynamics: What's in It for Healthcare Simulation Modelers." In *Proceedings of the 2008 Winter Simulation Conference*, edited by S. J. Mason, R. R. Hill, L. Mönch, O. Rose, T. Jefferson, and J. W. Fowler, 1478–1483. Piscataway, New Jersey: Institute of Electrical and Electronics Engineers, Inc.

Brailsford, S. 2015. "Hybrid Simulation in Healthcare: New Concepts and New Tools." In *Proceedings of the 2015 Winter Simulation Conference*, edited by L. Yilmaz, W. K V. Chan, I. Moon, T. M. K. Roeder, C. Macal, and M. D. Rossetti, 1689–1699. Piscataway, New Jersey: Institute of Electrical and Electronics Engineers, Inc.

Brailsford, S., P. R. Harper, B. P., and M. Pitt. 2009. "An Analysis of the Academic Literature on Simulation and Modelling in Health Care." *Journal of Simulation* 3 (3): 130–40.

Cabrera, E., E. Luque, M. Tboada, F. Epelde, and M. L. Iglesias. 2012. "ABMS Optimization For Emergency Departments." In *Proceedings of the 2012 Winter Simulation Conference*, edited by C. Laroque, J. Himmelspach, R. Pasupathy, O. Rose, and A. M. Uhrmacher, 1003–1014. Piscataway, New Jersey: Institute of Electrical and Electronics Engineers, Inc.

Chahal, K., and T. Eldabi. 2008. "Applicability of Hybrid Simulation to Different Models of Governance in UK Healthcare." In *Proceedings of the 2008 Winter Simulation Conference*, edited by S. J. Mason, R. R. Hill, L. Mönch, O. Rose, T. Jefferson, and J. W. Fowler, 1469–1477. Piscataway, New Jersey: Institute of Electrical and Electronics Engineers, Inc.

Dibble, C. 2010. "Effective Real-Time Allocation Of Pandemic Interventions." In *Proceedings of the 2010 Winter Simulation Conference*, edited by B. Johansson, S. Jain, J. Montoya-Torres, J. Hugan, and E. Yücesan, 135–150. Piscataway, NJ: Institute of Electrical and Electronics Engineers, Inc.

Djanatliev, A., and R. German. 2013. "Prospective Healthcare Decisions-Making by Combined System Dynamics, Disrete-Event and Agent-Based Simulation." In *Proceedings of the 2013 Winter Simulation Conference*, edited by R. Pasupathy, S.-H. Kim, A. Tolk, R. Hill, and M. E. Kuhl, 270–281. Piscataway, New Jersey: Institute of Electrical and Electronics Engineers, Inc.

Eldabi, T. 2009. "Implementation Issues of Modeling Healthcare Problems: Misconceptions and Lessons." In *Proceedings of the 2009 Winter Simulation Conference*, edited by M. D. Rossetti, R. R. Hill, B. Johansson, A. Dunkin, and R. G. Ingalls, 1831–1839. Piscataway, New Jersey: Institute of Electrical and Electronics Engineers, Inc.

Fakhimi, M., and N. Mustafee. 2012. "Application Of Operations Research Within The Uk Healthcare Context." In *Proceedings of the Operational Research Society Simulation Workshop*, edited by D-J. van der Zee B.Tjahjono, C. Heavey, S. Onggo.

Ferranti, J. S., and P. J. Freitas Filho. 2011. "Dynamic Mortality Simulation Model Incorporating Risk Indicators for Cardiovacular Diseases." In *Proceedings of the 2011 Winter Simulation Conference*, edited by S. Jain, R. R. Creasey, J. Himmelspach, K. P. White, and M. Fu, 1263–1274. Piscataway, New Jersey: Institute of Electrical and Electronics Engineers, Inc.

Fone, D., S. Hollinghurst, M. Temple, A. Round, N. Lester, A. Weightman, K. Roberts, E. Coyle, G. Bevan, and S. Palmer. 2003. "Systematic Review of the Use and Value of Computer Simulation Modelling in Population Health and Health Care Delivery." *Journal of Public Health* 25 (4): 325–35.

Gao, A., N. D. Osgood, W. An, and R. F. Dyck. 2014. "A Tripartite Hybrid Model Architecture for Investigating Health and Cost Impacts and Intervention Tradeoffs for Diabetic End-Stage Renal Disease." In *Proceedings of the 2014 Winter Simulation Conference*, edited by A. Tolk, S. Y. Diallo,

I. O. Ryzhov, L. Yilmaz, S. Buckley, and J. A. Miller, 1676–1687. Piscataway, New Jersey: Institute of Electrical and Electronics Engineers, Inc.

Giachetti, R. E., E. A. Centeno, M. A. Centeno, and Ramakrishnan Sundaram. 2005. "Assessing The Viability Of An Open Access Policy In An Outpatient Clinic: A Discrete-Event and Continuous Simulation Modeling Approach." In *Proceedings of the 2005 Winter Simulation Conference*, edited by M. E. Kuhl, N. M. Steiger, F. B. Armstrong, and J. A. Joines, 2246–2255. Piscataway, New Jersey: Institute of Electrical and Electronics Engineers, Inc.

Hagtvedt, R., M. Ferguson, P. Griffin, G. T. Jones, and P. Keskinocak. 2009. "Cooperative Strategies to Reduce Ambulance Diversion." In *Proceedings of the 2009 Winter Simulation Conference*, edited by M D. Rossetti, R. R. Hill, B. Johansson, A. Dunkin, and R. G. Ingalls, 1861–1874. Piscataway, New Jersey: Institute of Electrical and Electronics Engineers, Inc.

Heath, S. K., S. Brailsford, A. Buss, and C. M. Macal. 2011. "Cross-Paradigm Simulation Modeling: Challenges and Successes." In *Proceedings of the 2011 Winter Simulation Conference*, edited by S. Jain, R.R. Creasey, J. Himmelspach, K.P. White, and M. Fu, 2783–2797. Piscataway, New Jersey: Institute of Electrical and Electronics Engineers, Inc.

Hosseini, N., and K. Taaffe. 2014. "Evaluation of Optimal Scheduling Policy for Accommodating Elective and Non-Elective Surgery via Simulation." In *Proceedings of the 2014 Winter Simulation Conference*, edited by A. Tolk, S. Y. Diallo, I. O. Ryzhov, L. Yilmaz, S. Buckley, and J. A. Miller, 1377–1386. Piscataway, New Jersey: Institute of Electrical and Electronics Engineers, Inc.

Jun, J., S. Jacobson, and J. Swisher. 1999. "Application of Discrete-Event Simulation in Health Care Clinics : A Survey." *Journal of the Operational Research Society* 50: 109–23.

Kasaie, P., D. W. Dowdy, and W. D. Kelton. 2014. "Estimating the Proportion of Tuberculosis Recent Transmission via Simulation." In *Proceedings of the 2014 Winter Simulation Conference*, edited by A. Tolk, S. Y. Diallo, I. O. Ryzhov, L. Yilmaz, S. Buckley, and J. A. Miller, 1469–1480. Piscataway, New Jersey: Institute of Electrical and Electronics Engineers, Inc.

Kasaie, P., W. D. Kelton, A. Vaghefi, and S. G. R. J. Naini. 2010. "Toward Optimal Resource-Allocation for Control of Epidemics: an Agent-Based-Simulation Approach." In *Proceedings of the 2010 Winter Simulation Conference*, edited by B. Johansson, S. Jain, J. Montoya-Torres, J. Hugan, and E. Yücesan, 2237–2248. Piscataway, New Jersey: Institute of Electrical and Electronics Engineers, Inc.

Lynch, C., J. Padilla, S. Diallo, J. Sokolowski, and C. Banks. 2014. "A Multi-Paradigm Modeling Framework for Modeling and Simulating Problem Situations." In *Proceedings of the 2014 Winter Simulation Conference*, edited by A. Tolk, S. Y. Diallo, I. O. Ryzhov, L. Yilmaz, S. Buckley, and J. A. Miller, 1688–1699. Piscataway, New Jersey: Institute of Electrical and Electronics Engineers, Inc.

Marshall, D. A, L. Burgos-liz, M. J. Ijzerman, N. D. Osgood, W. V. Padula, M. K. Higashi, P. K. Wong, K. S. Pasupathy, and W. Crown. 2015. "Applying Dynamic Simulation Modeling Methods in Health Care Delivery Research — The SIMULATE Checklist : Report of the ISPOR Simulation Modeling Emerging Good Practices Task Force." *Value in Health.* 18: 5–16.

McGarvey, B. M., N. J. Dynes, B. C. Lin, W. H. Anderson, J. P. Kremidas, and J. Feli. 2007. "A Discrete Event Model Of Clinical Trial Enrollment At Eli Lilly and Company." In *Proceedings of the 2007 Winter Simulation Conference*, edited by S. G. Henderson, B. Biller, M.-H. Hsieh, J. Shortle, J. D. Tew, and R. R. Barton, 1467–1474. Piscataway, New Jersey: Institute of Electrical and Electronics Engineers, Inc.

Mustafee, N., L. Davies, T. Lyons, M. Ramsey, P. Rees, and M. D. Williams. 2012. "Planning of Bed Capacities in Specialized and Integrated Care Units: Incorporating Bed Blockers in a Simulation of Surgical Throughput." In *Proceedings of the 2012 Winter Simulation Conference*, edited by C. Laroque, J. Himmelspach, R. Pasupathy, O. Rose, and A. M. Uhrmacher, 835–846. Piscataway, New Jersey: Institute of Electrical and Electronics Engineers, Inc.

Mustafee, N., J. Powell, S. Brailsford, S. Diallo, J. Padilla, and A. Tolk. 2015. "Hybrid Simulation Studies and Hybrid Simulation Systems: Definitions, Challenges, and Benefits." In *Proceedings of* *the 2015 Winter Simulation Conference*, edited by L. Yilmaz, I. C. Moon, W. K. V. Chan, T. M. K. Roeder, C. M. Macal, and M. D. Rossetti, 1678–1692. Piscataway, New Jersey: Institute of Electrical and Electronics Engineers, Inc.

Onggo, B. S. 2014. "Elements of a Hybrid Simulation Model: A Case Study of the Blood Supply Chain in Low- and Middle-Income Countries." *Proceedings of the 2014 Winter Simulation Conference*, edited by A. Tolk, S. Y. Diallo, I. O. Ryzhov, L. Yilmaz, S. Buckley, and J. A. Miller, 1597–1607. Piscataway, New Jersey: Institute of Electrical and Electronics Engineers, Inc.

Ozaltin, O. Y., O. O. Dalgic, and F. Erenay. 2014. "Optimal Distribution of the Influenza Vaccine." In *Proceedings of the 2014 Winter Simulation Conference*, edited by A. Tolk, S. Y. Diallo, I. O. Ryzhov, L. Yilmaz, S. Buckley, and J. A. Miller, 1411–1420. Piscataway, New Jersey: Institute of Electrical and Electronics Engineers, Inc.

Pearce, B., N. Hosseini, K. Taaff, N. Huynh, and S. Harris. 2010. "Modeling Interruptions and Patient Flow in a Preoperative Hospital Environment." In *Proceedings of the 2010 Winter Simulation Conference*, edited by B. Johansson, S. Jain, J. Montoya-Torres, J. Hugan, and E. Yücesan, 2261–2270. Piscataway, New Jersey: Institute of Electrical and Electronics Engineers, Inc.

Rashwan, W., M. Ragab, W. Abo-Hamad, and A. Arisha. 2013. "Evaluating Policy Interventions for Delay Discharge: A System Dynamics approach." In *Proceedings of the 2013 Winter Simulation Conference*, edited by R. Pasupathy, S.-H. Kim, A. Tolk, R. Hill, and M. E. Kuhl, 2463–2474. Piscataway, New Jersey: Institute of Electrical and Electronics Engineers, Inc.

Standridge, C., C. Macal, A. A. B. Pritsker, H. Delcher, and R. Murray. 1977. "A Simulation Model Of The Primary Health Care System Of Indiana." In *Proceeding of the 1977 Winter Simulation Conference*. Piscataway, New Jersey: Institute of Electrical and Electronics Engineers, Inc.

Viana, J. 2014. "Reflections On Two Approaches To Hybrid Simulation In Healthcare." In *Proceedings of the 2014 Winter Simulation Conference*, edited by A. Tolk, S. Y. Diallo, I. O. Ryzhov, L. Yilmaz, S. Buckley, and J. A. Miller, 2600–2608. Piscataway, New Jersey: IEEE, Inc.

Vila-Parrish, A. R., J. S. Ivy, and R. E. King. 2008. "A Simulation-Based Approach For Inventory Modeling Of Perishable Pharmaceuticals." In *Proceedings of the 2008 Winter Simulation Conference*, edited by S. J. Mason, R. R. Hill, L. Mönch, O. Rose, T. Jefferson, and J. W. Fowler, 1532–1538. Piscataway, New Jersey: Institute of Electrical and Electronics Engineers, Inc.

Zeigler, B. P., H. Praehofer, and T. G. Kim. 2000. *Theory of Modeling and Simulation: Integrating Discrete Event and Continuous Complex Dynamic Systems*. 2nd Editio. Academic Press.

Zulkepli, J. and T. Eldabi. 2015. "Towards A Framework For Conceptual Model Hybridization In Healthcare." In *Proceedings of the 2015 Winter Simulation Conference*, edited by L. Yilmaz, W. K. V. Chan, I. Moon, T. M. K. Roeder, C. Macal, and M. D. Rossetti, 1–5. Piscataway, New Jersey: Institute of Electrical and Electronics Engineers, Inc.

Zulkepli, J., T. Eldabi, and N. Mustafee. 2012. "Hybrid Simulation For Modelling Large Systems: An Example Of Integrated Care Model." In *Proceedings of the 2012 Winter Simulation Conference*, edited by C. Laroque, J. Himmelspach, R. Pasupathy, O. Rose, and A.M. Uhrmacher, 1–12. Piscataway, New Jersey: Institute of Electrical and Electronics Engineers, Inc.

AUTHOR BIOGRAPHIES

AMR ARISHA, PhD is the Director of the 3S Group and Head of the Department of International Business in the College of Business at Dublin Institute of Technology (DIT). His research interests include analysis and optimization of complex dynamic systems in manufacturing and service industries. amr.arisha@dit.ie.

WAEL RASHWAN, MSc is a senior researcher in the 3S Group – DIT. He has a BSc and MSc in Operations Research (Cairo University), as well as extensive experience in industry. His research interests include: modelling and simulation, optimization, game theory and probability collectives. wael.rashwan@dit.ie.