Multi-Paradigm Modeling and Simulation in Health Care

Nikolaus Furian, Dietmar Neubacher, Siegfried Vössner, Michael O'Sullivan, Cameron Walker.

Abstract— **Demands on public health care systems have been constantly increasing over the last years - especially in quality and availability of care. To meet these demands it is important to develop efficient processes, resource allocations and management strategies. Modeling and simulation plays a major role in the accomplishment of these challenges. This paper gives a general introduction on benefits and possibilities of modeling and simulation approaches in health care by discussing the most commonly used methods and techniques including Discrete Event Simulation (DES), Agent-Based Simulation (ABS) and System Dynamics (SD). Based on essential deficiencies of single methods, hybrid approaches are identified as the biggest opportunity and at the same time challenge in the field of modeling and simulation – both in conceptual and practical terms. Combinations of accepted and mature techniques enable possibilities to study real systems on various levels. The relevance and need for such approaches is shown on a simple use case example which discusses spreading of virus-like diseases in crowded, confined areas like hospital waiting rooms.**

Key Words—**Agent-Based Simulation, Discrete Event Simulation, Health Care, Hybrid Simulation approach**

I. Introduction

Simulation models describe and abstract complex real world systems and thereby give a better insight and understanding of them. Mostly, they have at least one of the two following purposes and goals: the first one is to analyze and explain system behavior and interactions and the second one is to run experiments or so called 'what if' scenarios on the system without affecting the real world.

While the first goal serves the purpose of enhancing the decision maker's understanding of the system itself, the second one can serve as a basis for decisions/actions which change the system behavior in a desired direction. Simulation therefore allows decision makers to experiment with an abstract model and not with the real world system itself. One example would be the problem of allocating resources to different departments of a hospital aiming for an allocation that ensures the highest quality of health care delivered. Trying different scenarios, or allocations, in the real world would mean hiring and firing specialists or at least changing staff rosters and shifting other resources from one department to the other over and over again. This would certainly yield very high costs, a big work load and lead to very frustrated employees. By contrast, a simulation model that describes the hospital sufficiently well would be able to simulate the outcomes of different allocations. Here the best solution could be found without influencing the real system.

Manuscript accepted March 13, 2014, by Prof. Helmut Zsifkovits

A. *Simulation in Health Care*

The health care industry has an enormous size in any developed country with billions of dollars spent every year. Its importance will gain additional significance due to the demographic changes in western-oriented societies. Fig. 1 shows the development of public spending on health care in Austria since 1990. Absolute spending almost tripled during that period, which corresponds to a growth from 6.1% to 8.4% of the GDB.

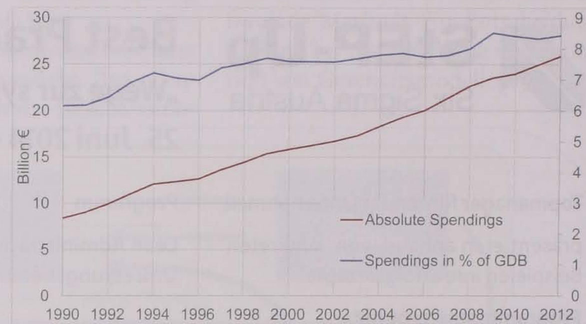

Fig. 1. Public Spending on Health Care in Austria, Source: Statistik Austria

Therefore, providing high quality services while keeping costs at a reasonable level is, and will be even more in the future, one of the most challenging tasks for both politicians and hospital managers as well as for doctors. Due to the ability to examine and validate important decisions in a virtual environment simulation can and should play a major role in that undertaking.

However, even though simulation has extensively been applied in industries like manufacturing, engineering, aerospace, the military and defense industry, its usage within the health care industry is not that widespread (Naseer et al. 2008; Kuljis et al. 2007).

The main reasons for the insufficient discussion of health care simulation are, according to the literature, the following; first, health care is a very diverse industry, with varying conditions over countries and types of care. Second, within health care there are usually many different stakeholders with different interests involved and last, investing money at an operations level is often seen as taking money away from medical care. However, the awareness of the importance and benefits of health care simulation has been growing rapidly over the last couple of years, as shown by a large number of simulation studies performed by a growing number of research institutions within and outside health care organizations.

B. From the Real World to a Simulation Model

Observations of current health care systems illustrate many challenging fields that models and simulations have to describe and explain properly. They reach from government policies and social trends, over preventive medical examinations strategies, up to the spread of virus-like diseases. Current state-of-the-art modeling and simulation paradigms are suitable for specific requirements regarding the level of detail and the availability of data. Throughout the development of a simulation the modeling process is one of the most important and many times underestimated procedures. The abstraction of a real system and the formulation of a conceptual model provide the basis for good research design (see Fig. 2). This process shows great impact in every upcoming phase, concerning definition of data requirements, development time, validation and experimentation (Robinson 2006).

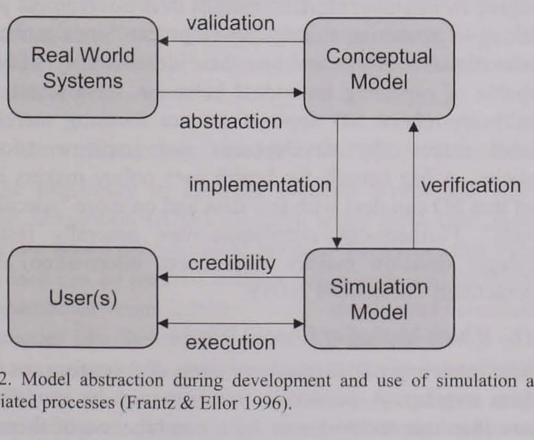

Fig. 2. Model abstraction during development and use of simulation and associated processes (Frantz & Ellor 1996).

The following chapter gives a brief explanation of the core concepts of commonly used simulation paradigms in health care and illustrates some related fields of application.

II. Common Modeling and Simulation Paradigms

The variety of different simulation paradigms and techniques is enormous and ranges from more technical ones like Finite Element Methods to more socio-economic explanatory approaches like System Dynamics. Five main categories of modeling and simulation techniques that are of significant importance for health care applications are the following: Discrete Event Simulation, Continuous Simulation, System Dynamics, Monte Carlo Simulation, Agent-Based Simulation and finally 3-D and Virtual Reality simulations (Kuljis et al. 2007).

A review of the existing literature on health care simulation studies and their results by Brailsford et al. (2009) showed that methods with significant share of usage and potential are mainly limited to Discrete Event, Agent-Based and System Dynamics. In the following paragraphs, the principles of these approaches are discussed.

A. Discrete Event Simulation (DES)

In DES the underlying system is changed at discrete points in time. How these changes are modelled, controlled and triggered depends on the sub-domain of discrete event simulation, also known as the "worldview"[1], being utilized. The classical world-views are: event scheduling; activity scanning; and process interaction:

1) Event Scheduling

As the name suggests, event scheduling is based on events that occur in a system. On its occurrence an event transforms the state of the system and possibly schedules future events. Thereby, future events are given a time stamp marking their occurrence in the timeline of the model. All future events are held in a list that is sorted by their time stamps. The simulation clock advances by choosing the earliest event in the list and updating the current time to the corresponding time stamp.

2) Activity Scanning and the Three Phase Approach

Activity Scanning focuses on activities that consist of a pair of events (start and end) and their preconditions. Time is increased incrementally and every time the simulation clock advances preconditions are evaluated and in case of a positive outcome corresponding activities are triggered. The Three-Phase Approach is a hybrid method of event scheduling and activity scanning that distinguishes between conditional and scheduled activities. Furthermore it incorporates both handling mechanisms, future event lists and an evaluation of preconditions.

3) Process Interaction

Processes define the stepwise simulated flow of an entity through the system. Process Interaction frameworks provide

[1] Remark: The Three Phase Method, which is an extension to the Activity Scanning approach, is often also referred to as a "world-view" (Silver et al. 2011)

a diverse set of handling methods for interaction of these processes and time advancement mechanisms.
Discrete Event Simulation is the oldest and most widespread simulation paradigm. It originates from the modeling of manufacturing layouts. Still most practical studies are published in this field, although other fields of applications, as health care, are rapidly growing. Based on its structure and history the strengths of DES are the design of operational, entity flow and process models.

B. *Agent-Based Modeling (ABM)*

Agent-Based Modeling and Simulation is a relatively new approach. In comparison to the other common techniques, agent-based modeling focuses on the micro level and represents individual behavior of single active entities. Due to the fact that this method was simultaneously developed by different scientific communities, a unique definition of the term "agent" is not available. However the following characteristics (Macal & North 2008) were compiled by collecting frequently used definitions and seem to be very useful: First, an entity has to fulfill certain fundamental criteria to be considered an agent, such as being an identifiable individual with a set of characteristics and rules which influence its behavior and decision making. Another criterion is the goal-orientation that is directly related to its behavior. Furthermore, an agent should be social and able to perceive, interact and communicate with other agents and its environment. Finally, an agent needs to be flexible and should have the ability to learn which therefore requires a certain form of memory. These properties and attributes can be subsumed as modularity, autonomy, sociality and conditionality (Macal & North 2013).
The simplest form of an agent-based simulation is an environment and a number of agents that are acting in it. Each agent has a state and a so called "logic", which is basically a set of rules. Depending on the intention, one can observe the overall system behavior which is emerging out of the individual interactions/decisions of the agents, the response of agents to changes of the environment or a mix of these aspects.
Applications of agent-based simulation cover a wide ranging field. This method still attracts more and more attention because of the availability of micro data (Onggo & Karpat 2011). New Information and Communication Technologies (ICT) provide an enormous amount of data and lead to a better description of individual behavior. Additionally the rapid growth in available computing power allows modelers to build over-proportionally larger and more complex agent-based models. Therefore the number of issues regarding large populations with many agents is on the rise. Applications in the field of health care increase as well and are usually related to simulations concerning the spread of diseases, patient flows and staff scheduling in emergency departments.

C. *System Dynamics (SD)*

SD is known as a powerful method to analyze, model and simulate dynamic and complex systems. Semi-informally speaking, system dynamic models consist of large scale continuous differential equation systems that are usually not solvable analytically. Hence, SD resolved this issue by simulating the equation rather than solving them. It is important to note that this method operates in continuous domains for time advancement, flows and stocks. One of the major advantages of SD is the ability to incorporate the complexity, non-linearity and feedback loop structure of real world dynamic systems. The main conceptual idea behind is that the structure of the system determines its behavior over time (Sterman 2000). Because of these characteristics SD is especially popular in the fields of social and physical systems.
SD is divided into a qualitative approach, also known as System Thinking (Richmond 1993), and a quantitative approach. Causal Loop Diagrams (CLD) are used to depict system structure by connecting relevant system elements via arrows. Added polarities illustrate the corresponding behavior between two connected elements. The complexity of a system does not arise from a single variable, but rather it is caused by the relationships between them. The dynamic behavior originates from two different types of feedback loops that can be either re-enforcing or balancing. Stock and flow diagrams are used in the quantitative area of SD and allow to depict a more detailed structure of the system. Stocks are accumulations of flows over time and represent the state of the system at any time throughout the simulation. Flows are representations of adjustable rates that are regulating the inflows or outflows of stocks.
SD is generally used to describe real world systems on an aggregated, macro level and to observe long term system behavior. Therefore, the area of its application is mainly ranging from global climatic models over government policy making to marketing strategy development. Since entities are accumulated in stocks and lose their identifiability, SD is not capable of capturing individual behavior. As a result, most healthcare-related SD applications are focusing merely on global issues like development and implementation of policies. A big benefit for health care policy makers is the fact that SD can deal with few data and on more "speculative levels". Furthermore, simulation runs generally fast and strategic decision makers can access information almost interactively (Brailsford 2008).

D. *Which Method to Choose When?*

These modeling paradigms have some disjoint features while others overlap. A particular problem may be modeled by more than one technique or by a combination of them (see Fig. 3). Recently, this has led to vivid discussions among scientists on the strength, weaknesses and suitable applications of all approaches (e.g.: Brailsford 2014; Siebers et al. 2010; Brailsford et al. 2010).

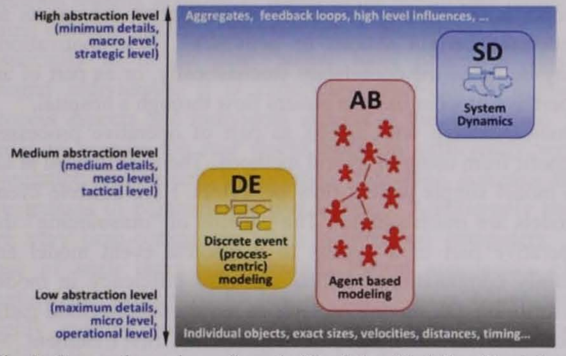

Fig. 3. Commonly used paradigms in Simulation Modeling (Borshchev & Filippov 2004).

Despite the scientific communities' awareness of the importance of choosing the right paradigm with respect to the underlying system, practitioners often tend to choose the method they are most comfortable, or have the most experience with (Siebers et al. 2010). This obviously leads to unnecessary complex and cumbersome models that, in the best case, are harder to design, explain, maintain and consume more computational resources or, in the worst case, result in failed simulation projects.

For large and complicated problems a single method often cannot cover all features of the real system. Therefore, a lot of work and research is currently done on combinations of approaches, so called hybrid or multi-paradigm methods.

Due to the high potential (Kuljis et al. 2007), the ongoing scientific discussion (Brailsford 2014; Siebers et al. 2010; Brailsford et al. 2010) and the authors' experiences in the related fields, the next section is proposing a combination of DES and ABS, which offers the possibility and benefits to include global trends and policies on a macro level. This paradigm is currently being investigated in several related research projects.

III. Multi Paradigm: Combining Different Approaches

The possibility to combine Discrete Event and Agent-Based Simulation (ABS) naturally arises from their similar structure based on individual entities. Therefore, this hybrid approach can be realized without major technical difficulties compared to combinations with continuous simulation techniques like System Dynamics. To the knowledge of the authors, no generally accepted framework for a combination of discrete and continuous simulation paradigms exists. These similar model structures can furthermore lead to easy model integration and a variety of synergy effects.

A. *Hybrid approaches in other fields*

The need for a combination of existing paradigms did not originally arise in the field of health care, but one of the publications attracting most attention, that proposed such an approach as a step towards the *Holy Grail* in simulation, was related to health care (Brailsford et al. 2010). In many applications over the last years the boundaries of a single approach have been continuously extended (Siebers et al. 2010) using Operations Research (OR) and DES. Simple passive entities were not capable to deal with the requirements of capturing the real system in an adequate level of detail. Therefore the term *entity* was sometimes already replaced by the term *pseudo agent*.

B. *Benefits and Needs to combine…*

One of the major benefits of the extension of DES with AB features is the possibility to illustrate and observe individual behavior that arises from the micro level during operational entity flow and process simulations. The dynamic complexity of sole DES is mainly based on queuing theory. Individuality of resources or entities is not being captured and stochastic effects are the only possibility to explain such issues. ABS is well suited to capture individual behavior and therefore adds new insights to models and simulations. A waiting room at the admission office should serve here as an illustrative example. An agent (i.e. patient) will go home with a probability of 50%, when he is still untreated after 1 hour. This situation could be easily modeled with DES alone. But adding a second rule to the agents' logic - like the probability of going home will rise to 75%, when at least one of the other waiting agents decides to go home - could cause problems for a DES modeler. This simple case should illustrate the benefit by connecting ABS to DES, and thereby being able to capture real behavior much more precisely.

Another benefit is the exploration of real systems at an appropriate level. As already mentioned, single techniques often lead to cumbersome models trying to fit as good as possible to the real situation. By combining suitable methods that perfectly fit the observed subsystem, the creation of proper models raises modeling quality, understanding of the system and credibility of the user and decision makers.

Despite the big advantages of combining ABS and DES, some challenges have not yet been overcome: First, the calculation effort increases rapidly and the performance of the simulation drops because of dealing with a huge number of entities (Gunal 2012). This especially affects ABS where the complexity of each agent is obviously greater than in DES. Second, the development of an ABS requires knowledge in object oriented software design and basic programming skills (Siebers et al. 2010). At last, the modeler tends to use a single method depending on his expertise and affinity. Depending on the viewpoint, systems can be seen as processes that change the state of entities or entities which are developing over time by taking part in activities.

When distinct behavior, interaction or communication between individuals becomes necessary, only ABS can satisfy these requirements adequately at the price of long simulation run times and other computational efforts. To keep these efforts in reasonable bounds, an efficient combination of both methods can be the key. Hybrid simulations can switch off time intensive tasks when not needed. Hence, if individual-based aspects are required at specific situations during the simulation, the entity should be placed into the environment and act like an agent. Throughout the rest of the simulation, where no individual behavior is needed, the entity behaves just like a passive object (including some attributes that are used to store the latest state of the corresponding agent). This reduction of complexity leads to a dramatic saving of computational effort which is directly related to computer runtime. Such a flexible usage of agent-based aspects promises to be a useful approach also to extend current implementations of sole DES patient flow simulations (Brailsford et al. 2013).

Finally another big advantage is related to the previously mentioned benefit regarding the exploration of real systems at an appropriate level and supports modelers during validation and verification of the model: Especially when dealing with specialized medical fields, related experts are needed to generate, review and calibrate the model. Large scale models connect various sub-domains together and therefore allow evaluating each subsystem with associated experts separately.

C. *Use Case (spreading viruses in waiting rooms)*

Modeling the spread of virus-like diseases is one of the classical use cases for agent-based modeling. Most diseases are transmitted by direct contact or airborne. In both cases an interaction of agents and a bidirectional information flow among them is necessary. This includes factors like distance and time of proximity. Hence, discrete event models can, if at all, hardly being tweaked to reflect such a real world behavior accurately. On the other hand, the agent-based paradigm provides all features to create elegant and lean representations where the spread of influenza like diseases need to be studied (Laskowski et al. 2011).

So far there seems to be no need for a hybrid method since all requirements are covered by the ABS paradigm. However, the movements and actions of agents need to follow processes and are part of a bigger system which we investigate with our simulation. This system can either exist on a micro, meso or macroscopic level. For example, the study of Laskowski et al. (2011) investigated an emergency department (microscopic), in other studies the actions and movements of agents are captured at a larger scale, for example at city or state level (macroscopic). For all levels of scope, it is necessary to model a motivation for agents to undertake certain actions or activities. These motivations may be modelled completely stochastically, or as part of an operative process like the patient flow through a hospital.

Studies dealing with agents as part of operative processes benefit from using of hybrid methods. There is no need at all to model simple patient flow behaviors. Here discrete event models are much simpler. The benefits of "outsourcing" the operative part of a system to a discrete event model are mainly computational efforts and also efficiency in model description. DE models are able to represent behavioral paths like "arrival → triage → register → first treatment → diagnostics → possible second treatment → dismissal" as in the model by Laskowski et al. (2011), which is one of the first published studies on this topic and considered to be highly innovative. The authors argue that their simulation runs consume a large amount of computational resources due to non-optimal design. Their experiments took over 1200 hours of CPU time. This might still be acceptable for smaller models but becomes a great issue for complex scenarios.

We are currently investigating the spread of influenza-like diseases in an integrated hospital layout, including emergency departments, diagnostic facilities, wards and outpatient clinics. Obviously, the operative segment of the model becomes relatively complex and any sole agent-based representation would result in intractable models which could hardly be simulated at all. Therefore, patient flows, treatments and movements between departments and clinics are handled by a discrete event simulation and the behavior of patients within waiting areas of the hospital are represented by an agent-based approach. The spread of diseases within waiting rooms is dependent on individual patients' movements, e.g. visiting bathrooms, picking up newspapers and choosing seats. Proximity and contact to other patients, as well as the duration of stay in the room are key factors for transmission and have to be modeled individually. On the other hand the behavioral pattern during certain activities, such as treatments or diagnostics, always consist of the same patterns with the same number and type of agents/entities. Hence, they might as well be represented by stochastic functions, since there is not an absolute need for the degree of accuracy an agent-based model would provide for these segments. As always, there is a trade-off between accuracy and computational costs. Currently we are developing a discrete event simulation to investigate the dynamics arising from interconnected departments. Simultaneously an agent based model is formed that will be connected to waiting rooms in the DE simulation.

IV. Conclusion

This article argues that there is a significant need to support decision making at different levels in the health care industry using efficient modeling and simulation techniques.

Especially in health care, where most processes center around individuals, it is especially important to capture process aspects and individual aspects at the same time. In order to capture the real world situation sufficiently well, simulation models tend to become rather large, complex and are tedious to parameterize and validate. Additionally they are very time-consuming when running on computers. In case of such large scale models hybrid approaches can capture the properties of real world systems better than highly customized single method approaches, which we outlined by using a simple case of viral disease transmissions within process-oriented environments like hospital facilities. We are currently investigating the benefits of such a hybrid design in several ongoing research projects in more detail.

References

1. Borshchev, A. & Filippov, A., 2004. From System Dynamics and Discrete Event to Practical Agent Based Modeling: Reasons, Techniques, Tools. In *Proceedings of the 22nd International Conference of the System Dynamics Society*.
2. Brailsford, S.C., 2014. Discrete-event is alive and kicking! *Journal of Simulation*, 8(1), pp.57–65.
3. Brailsford, S.C. et al., 2013. Hybrid simulation for health and social care: The way forward, or more trouble than it's worth? In *Proceedings of the 2013 Winter Simulation Conference*. pp. 258–269.
4. Brailsford, S.C., 2008. System dynamics: What's in it for healthcare simulation modelers. In *Proceedings of the 2008 Winter Simulation Conference*. pp. 1478–1483.
5. Brailsford, S.C., Desai, S.M. & Viana, J., 2010. Towards the holy grail: Combining system dynamics and discrete-event simulation in healthcare. In *Proceedings of the 2010 Winter Simulation Conference*. pp. 2293–2303.
6. Frantz, F.K. & Ellor, A.J., 1996. *Model Abstraction Techniques*, Rome Laboratory Technical Report.
7. Gunal, M.M., 2012. A guide for building hospital simulation models. *Health Systems*, 1(1), pp.17–25.
8. Kuljis, J., Paul, R.J. & Stergioulas, L.K., 2007. Can health care benefit from modeling and simulation methods in the same way as business and manufacturing has? In *Proceedings of the 2007 Winter Simulation Conference*. pp. 1449–1453.
9. Laskowski, M. et al., 2011. Agent-Based Modeling of the Spread of Influenza-Like Illness in an Emergency Department: A Simulation Study. *IEEE Transactions on Information Technology in Biomedicine*, 15(6), pp.877–889.
10. Macal, C.M. & North, M.J., 2008. Agent-based modeling and simulation: ABMS examples. In *Proceedings of the 2008 Winter Simulation Conference*. pp. 101–112.
11. Macal, C.M. & North, M.J., 2013. Introductory tutorial: Agent-based modeling and simulation. In *Proceedings of the 2013 Winter Simulation Conference*. pp. 362–376.
12. Naseer, A. et al., 2008. Potential applications of simulation modeling techniques in healthcare: Lessons learned from aerospace and military. In *Proceedings of the European and Mediterranean Conference on Information Systems*.
13. Onggo, B.S.S. & Karpat, O., 2011. Agent-based conceptual model representation using BPMN. In *Proceedings of the 2011 Winter Simulation Conference*. pp. 671–682.
14. Richmond, B., 1993. Systems thinking: Critical thinking skills for the 1990s and beyond. *System Dynamics Review*, 9(2), pp.113–133.
15. Robinson, S., 2006. Conceptual modeling for simulation: issues and research requirements. In *Proceedings of the 2006 Winter Simulation Conference*. pp. 792–800.
16. Siebers, P.O. et al., 2010. Discrete-event simulation is dead, long live agent-based simulation! *Journal of Simulation*, 4(3), pp.204–210.
17. Silver, G.A. et al., 2011. DeMO: An Ontology for Discrete-event Modeling and Simulation. *SIMULATION*, 87(9), pp.747–773.
18. Sterman, J.D., 2000. *Business dynamics - systems thinking and modeling: for a complex world*, McGraw-Hill Higher Education.

NIKOLAUS FURIAN is a visiting post-doc at the Department of Engineering Science, University of Auckland, New Zealand. He obtained his degree in Technical Mathematics at the University of Technology Graz in 2008. During his PhD program he focused on applied Operations Research topics, especially bin packing. Currently he is working on simulation and optimization applications in the health care sector.

E-mail: `nfur003@aucklanduni.ac.nz`.

DIETMAR NEUBACHER is a Research Assistant at Graz University of Technology and studied Mechanical Engineering and Business Economics at the same University. He gained his master degree in 2012 and is currently working on his PhD thesis at the department of Engineering- and Business Informatics with a research focus on the opportunities of hybrid and multi-paradigm modeling and simulation.

E-mail: `dietmar.neubacher@tugraz.at`

SIEGFRIED VÖSSNER holds a PhD degree in Engineering Sciences from Graz University of Technology. Until 1999 he was a postdoctoral fellow and visiting scholar at the Department for Engineering Economic Systems and Operations Research at Stanford University, USA. After being with McKinsey & Company he became professor and chairman of the Department of Engineering- and Business Informatics in 2003 and is currently Vice-Dean of the School of Mechanical Engineering and Economic Sciences of Graz University of Technology.

E-mail: `voessner@tugraz.at`

MICHAEL O'SULLIVAN is a Senior Lecturer in the Department of Engineering Science at the University of Auckland, New Zealand. He received his PhD in Management Science and Engineering from Stanford University. He works on Operations Research (OR) modeling, applications and computation. His current focus is the use of OR to build intelligent cloud systems and improve health care systems.

E-mail: `michael.osullivan@auckland.ac.nz`.

CAMERON WALKER is a Senior Lecturer in the Department of Engineering Science at the University of Auckland, New Zealand. He received his PhD in Mathematics from the University of Auckland. He works on computational analytics, focusing on statistical modelling, simulation and optimization.

E-mail: `cameron.walker@auckland.ac.nz`.