Applying the stress guidelines for reproducibility in modeling & simulation: Application to a disease modeling case study

This item was submitted to Loughborough University’s Institutional Repository by the/an author.

Citation: TAYLOR, S.J. ... et al., 2019. Applying the stress guidelines for reproducibility in modeling & simulation: Application to a disease modeling case study. Presented at the Winter Simulation Conference (WSC), Gothenburg, 9-12th December pp. 739 - 748.

Additional Information:

• Personal use of this material is permitted. Permission from IEEE must be obtained for all other uses, in any current or future media, including reprinting/republishing this material for advertising or promotional purposes, creating new collective works, for resale or redistribution to servers or lists, or reuse of any copyrighted component of this work in other works.

Metadata Record: [https://dspace.lboro.ac.uk/2134/37810](https://dspace.lboro.ac.uk/2134/37810)

Version: Accepted for publication

Publisher: © IEEE

Please cite the published version.
GUIDELINES FOR REPRODUCIBILITY IN MODELING & SIMULATION: 
THE STRENGTHENING THE REPORTING OF EMPIRICAL SIMULATION STUDIES 
(STRESS) APPROACH

Simon J. E Taylor
Anastasia Anagnostou

Modelling & Simulation Group
Department of Computer Science
Brunel University London
Uxbridge, UB8 3PH, UK

Thomas Monks
Christine Currie

University of Southampton
SO17 1BJ, Southampton, UK

Bhakti Stephan Onggo
Martin Kunc

Trinity Business School
Trinity College Dublin
Dublin, Ireland

Warwick Business School
University of Warwick
Coventry, CV4 7AL, UK

Stewart Robinson
School of Business and Economics
Loughborough University
Loughborough, LE11 3TU, UK

ABSTRACT

It is arguably difficult to reproduce the results of published work in Modeling & Simulation (M&S). Authors have certainly raised concerns about this issue and attempts by journals and conferences are being made to improve the situation. To help to improve reproducibility in M&S we present the Strengthening The Reporting of Empirical Simulation Studies (STRESS) checklists for reproducibility. These have three types: Discrete-Event Simulation (DES), System Dynamics (SD) and Agent Based Simulation (ABS). The paper first reviews the evidence for a simulation reproducibility crisis. The STRESS guidelines are then introduced with high level reporting principles for simulation studies. A short case study gives an example of how STRESS could be used in an artificial case study in ABS. It is hoped that widespread acceptance of STRESS will go some way to helping increase reproducibility in M&S.

1 INTRODUCTION

Why should we be worried about reproducibility? Have you ever tried to reproduce the results from a simulation paper? How easy is it to get the data, results, model, software, etc.? Let’s assume that you have downloaded a paper with results from a simulation study. You are interested as you would like to understand what the authors have done so that you can repeat it yourself and use their approach and results in your own work (with appropriate citations). Although some model data, detail and results are described and discussed in the paper, there is not enough to work with. You try to find out more information by following the authors’ publications. Some of their articles do give more details but
frustratingly you still do not have a complete picture. You contact the authors directly but it has been some years since the work and, remarkably, no one has any idea where the data, model or results are.

This is not a “simulation only” problem. There have been recent articles in the scientific press raising concerns about the lack of reproducibility in science. For example, a recent survey in Nature suggested that around 50% of scientists believed there is a substantial reproducibility ‘crisis’ (Baker 2016). Studies in Modeling & Simulation (M&S) relating to reproducibility have also raised this issue (e.g. detailed reviews of published models (Rahmandad and Sterman 2012; Janssen 2017) to tasking teams to reproduce model results (Boylan et al. 2015)). Actions are being taken to take reproducibility seriously in our community. For example, the journal ACM Transactions on Modelling and Computer Simulation now provides an optional reproducibility review for submitted models as does the ACM SIGSIM PADS conference. This “peer-review” of results will give a “seal of reproducibility”. However it may not give researchers the necessary documentation needed to independently reproduce the contents of a paper.

To attempt to frame how simulation studies could be reported in a standard way, we have created a set of reporting guidelines that could be used to aid the reproducibility of simulation studies. These are the Strengthening The Reporting of Empirical Simulation Studies (STRESS) checklists for reproducibility (Monks, et al. 2018). These take the form of three “templates” for reporting Discrete-Event Simulation (DES), System Dynamics (SD) and Agent Based Simulation (ABS) studies. The templates are freely downloadable from (https://eprints.soton.ac.uk/407453/).

The paper gives an overview of STRESS. We first review the evidence for a simulation reproducibility crisis. The STRESS guidelines are then introduced with high level reporting principles for simulation studies. We then give a short example of how STRESS could be used. Note that a wider discussion of how STRESS could be used in Open Science is given in (Taylor, et al. 2017).

2 A REPRODUCIBILITY CRISIS IN M&S?

There is growing evidence of poor reproducibility of simulation studies. Three key studies give a “flavor” of the problem that our community faces.

Rahmandad and Sterman (2012) sampled a year’s worth of articles from the academic journal System Dynamics Review. There were 27 papers that reported an SD model and scientific result. Out of 27 models, 16 (59%) included no equations at all while 2 (7%) reported ‘some’ equations. The set of equations that define the flow rates between stocks are pivotal to a quantitative SD model. Without these equations the model cannot be reproduced. If we consider another basic tenant of reproducibility – data – only 8 (30%) included the parameter values to reproduce the base case results.

Janssen (2017) investigated the reproducibility of 2367 ABS models returned from a search of ISI Web of Science. The study found that 50% of publications report complete or ‘some’ equations. The authors’ particular interest was access to model source code. Findings were that source code for the models was only available for 10% of the publications, although this appears to be slowly increasing. The authors note that the lack of transparency in how models work is slowing down knowledge creation and leads to duplication of effort in research.

We found no overarching review of DES reporting, but Kurkowski et al. (2005) reviewed 114 DES models of Mobile Ad Hoc Networks (MANETS). They summarized the ‘common pitfalls’ found in the reporting of these models and concluded that the majority of studies were not reported completely and hence cannot be reproduced by other researchers. Some key findings were that 58% of the studies did not specify if a model was terminating or steady state; 0% of studies detailed the pseudo random number generator included; 93% of studies did not include any comment on the need to deal with initialization bias and the 7% that did failed to provide any documentation about the analysis procedure used to select a warm-up period; finally 25% of studies did not state the simulation software in which the model was implemented.

Beyond this Levent Yilmaz (Yilmaz et al. 2014) noted the critical role of reproducibility in M&S as well as automated provenance tracking, discoverability across the artifacts of M&S research and the
appropriate use of Creative Commons licenses. Indeed he argues that reproducibility is key to credibility in research. The benefits of good reproducibility practice might also include:

- The advancement of operational knowledge (through reusing a published model to further investigate a system);
- To enable reuse of knowledge (models are expensive to develop; reusing models (or model components) can save time and money in M&S projects that could be devoted to a wider ranging study or analysis forms);
- To further conceptual modelling knowledge (a published model will argue how a conceptualization of a system has led to a given model, simulation, results and analysis; accurately reporting this conceptualization will help other researchers tackling similar problems in deciding what to model and what not to model;
- To reuse data where none exists (in many M&S projects data cannot be collected or is limited. In this case expert opinion is captured and modelled and/or missing data is approximated; capturing these assumptions in systematic manner will help to understand the validity of the study and help others to understand and build on the techniques used); and
- Testing of novel simulation methods (the validation of new analysis methods, algorithms, experimentation techniques require careful specification so that they can be assessed and reused elsewhere).

3 EXISTING APPROACHES TO SIMULATION REPORTING

Table 1 lists seven reporting guidelines relevant to simulation within Operational Research/Management Science (OR/MS) published since 1984 with the applicable M&S type as well as key strengths and weaknesses. Reference to any of the guidelines will undoubtedly strengthen the reporting of simulation studies. The guidelines vary in detail and relevance. For example, limited to visualization (Karnon et al. 2012), optimization aspects of simulation (Kendall et al. 2016), high level considerations (Waltemath et al. 2011) or domain specific (Husereau et al. 2013). Key guidance for SD is given in Rahmandad and Sterman (2012) and for ABS (from an Ecology perspective) is given in Grimm et al. (2006). One weakness of this literature is that it is disparate and apart from one case outside of OR/MS. There is no single framework that unifies DES, ABS and SD reporting guidance for OR/MS. The most comprehensive guidelines also suffer from the lack of a simple checklist that a modeler/author can reference. Most reporting guidelines are constructed in this format.

4 GUIDELINES FOR REPRODUCIBILITY IN M&S

The STRESS checklist attempts to provide authors with a framework to capture relevant details of a simulation study in such a way to enable others to validate and to reuse and extend the work of others. The STRESS guidelines were developed from (1) a literature review of good practice reporting approaches within OR/MS, scientific model-based/empirical disciplines and software engineering; (2) M&S community engagement; and (3) expert review.

Table 2 shows the general STRESS checklist. These are split into sections: objectives, model logic, data, experimentation and implementation. There are three specific instances of STRESS reflecting different M&S paradigms (agent-based simulation, discrete-event simulation and system dynamics): STRESS-ABS, STRESS-DES and STRESS-SD, respectively. Hybrid and/or distributed simulations can use these guidelines by combining STRESS guidelines to reflect the different paradigms used. Full STRESS definitions are accessible in Monks, et al 2018. We briefly discuss each section in turn.
4.1 Objectives

Objectives contain three items that define what the study aims to achieve. These are:

- **purpose** and rationale for the project including the model’s intended use or experimental frame to aid other researchers and modelers understand the choices made in conceptualizing the model;
- **model outputs** that the model will predict; and
- **aims of experimentation**, specific information about how the model is being used to achieve the stated purpose.
4.2 Logic

Logic specifies model logic and logic used in scenarios (if applicable) described in terms of several items. Given the wide range of M&S approaches, STRESS recommends the use of a recognized diagramming approach that is meaningful to the community of practice in which simulation is applied as an aid to communicate model design. Within the main text authors should limit diagrams to conceptual or simplified overviews. Complex diagrams used to communicate complete model design should be included as supplementary appendix material. Components refer to the basic conceptual building blocks of the model and reflects the type of M&S paradigm: STRESS-DES focusses on entities, activities, resources and queues; STRESS-ABS focuses on the environment, agents, topology and interaction; and STRESS-SD focuses on stocks, flows and feedback loops.

<table>
<thead>
<tr>
<th>Section</th>
<th>Item No.</th>
<th>Checklist item</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. Objectives</td>
<td>1.1</td>
<td>Purpose of the model</td>
</tr>
<tr>
<td></td>
<td>1.2</td>
<td>Model Outputs</td>
</tr>
<tr>
<td></td>
<td>1.3</td>
<td>Experimentation Aims</td>
</tr>
<tr>
<td>2. Logic</td>
<td>2.1</td>
<td>Base model overview diagram</td>
</tr>
<tr>
<td></td>
<td>2.2</td>
<td>Base model logic</td>
</tr>
<tr>
<td></td>
<td>2.3</td>
<td>Scenario logic</td>
</tr>
<tr>
<td></td>
<td>2.4</td>
<td>Algorithms</td>
</tr>
<tr>
<td></td>
<td>2.5</td>
<td>Components</td>
</tr>
<tr>
<td>3. Data</td>
<td>3.1</td>
<td>Data sources</td>
</tr>
<tr>
<td></td>
<td>3.2</td>
<td>Input parameters</td>
</tr>
<tr>
<td></td>
<td>3.3</td>
<td>Pre-processing</td>
</tr>
<tr>
<td></td>
<td>3.4</td>
<td>Assumptions</td>
</tr>
<tr>
<td>4. Experimentation</td>
<td>4.1</td>
<td>Initialization</td>
</tr>
<tr>
<td></td>
<td>4.2</td>
<td>Run length</td>
</tr>
<tr>
<td></td>
<td>4.3</td>
<td>Estimation approach</td>
</tr>
<tr>
<td>5. Implementation</td>
<td>5.1</td>
<td>Software or programming language</td>
</tr>
<tr>
<td></td>
<td>5.2</td>
<td>Random sampling</td>
</tr>
<tr>
<td></td>
<td>5.3</td>
<td>Model execution</td>
</tr>
<tr>
<td></td>
<td>5.4</td>
<td>System specification</td>
</tr>
</tbody>
</table>

4.3 Data

What data is used in the simulation? There are many different forms of data. For example, data sources (spreadsheets, databases, sensors, etc.), input parameters for base runs of the model and scenario experiments, derived distributions as well as associated data pre-processing and assumptions. Recommendations for reporting model data are common across the three modelling disciplines. There may be instances of modelling research where data is confidential or there are commercial reasons why data cannot be published. Ideally in these cases, descriptions should include hypothetical non-proprietary data so that researchers can still verify that a model has been reproduced accurately. Ethical considerations may also apply and should be mentioned with any sensitive data (especially with respect to health systems).

4.4 Experimentation

Experimentation deals with how the model was initialized, its run length and the output estimation approach used. In DES, initialization might capture warm-up periods, warm-up analysis procedures and
procedures for setting initial conditions for queues and activities are reported. In SD, the initial values of stocks might be considered. In ABS, the initial agent population size and attribute values and environment setup might be captured. Output estimation approach would depend on if the model was deterministic or stochastic. (e.g. the number of replications; use of variance reduction techniques such as common random numbers or antithetic variates, etc.) Results could be presented here (through a link) if not clear in the accompanying paper.

4.5 Implementation

This captures the implementation of the model/simulation. Software refers to the commercial or open source software, simulation or general purpose programming language or any other form of technology used to implement the model/simulation covered by the previous items (with the version numbers and any additional information needed to install/execute the software). Random sampling details should be captured if the model is stochastic. The implementation of variance reduction techniques should also be considered. For example, in the case of common random numbers authors should describe how streams or seeds are distributed across components within the model. Model execution refers to how simulated time progresses within the model (which varies across the three approaches). Hardware and runtime information are important to capture the environment in which the (potentially distributed) model/simulation runs (especially if cloud, grid or high performance computing is used).

5 STRESS: A CASE STUDY

To illustrate how STRESS can be used to document a simulation study, we use an agent-based infection model implemented in REPAST (repast.github.io) introduced to illustrate approaches to Open Science in M&S (Fabiyi, et al. 2016; Taylor, et al. 2017). This “studies” the spread of infection in a population after an outbreak. Agents can be infected, susceptible or recovered. When an infected agent approaches a susceptible agent, the latter becomes infected and if there are more than one susceptible agent in the cell, only one, randomly selected agent, is infected. Infected agents recover after a period and become recovered with a level of immunity. Recovered agents immunity decreases every time they are approached by an infected agent and when immunity becomes zero, the recovered agent becomes susceptible and can be infected again, thereby, forming a host of infection networks. The input parameters for the model include:

- simulation period (specifies how many years the simulation will run);
- recovered count (specifies the initial recovered population);
- infected count (specifies the initial infected population); and
- susceptible count (specifies the initial susceptible population).

We ran five experiments to produce five sets of results. We also created a simple visualization tool that allows easy analysis of infected/non-infected population trends. Following good Open Science practices, the model, results, visualization tool and summary pack have been deposited in an open access repository and assigned Digital Object Identifiers (DOIs) as follows:

- REPAST Infection Model Example DOI Collection (summary pack) https://dx.doi.org/10.15169/sci-gaia:1457690398.43
- REPAST Infection Model Virtual Appliance https://dx.doi.org/10.15169/sci-gaia:1455182324.71
- Graphical Visualization Tool for REPAST Infection Model https://dx.doi.org/10.15169/sci-gaia:1457432416.29
- REPAST Infection Model Experiment 1 Results https://dx.doi.org/10.15169/sci-gaia:1457431676.23
CONCLUSIONS

This paper has discussed why as a M&S community we might be concerned about reproducibility. Authors have raised concerns about this issue and attempts by journals and conferences are being made to improve the situation. To help to improve reproducibility in M&S, building on recommendations and existing guidelines we have presented the Strengthening The Reporting of Empirical Simulation Studies (STRESS) checklists for reproducibility. These have three types: Discrete-Event Simulation (DES), System Dynamics (SD) and Agent Based Simulation (ABS). The templates are freely downloadable from (https://eprints.soton.ac.uk/407453/). This paper has given a short example of how STRESS could be used in an artificial case study in agent-based simulation.

Reproducibility of results is one aspect of Open Science, a “movement” that encourages the digital sharing of the scientific artefacts. While reproducibility is important, we hope that our community will encourage the appropriate open sharing of models, data, results and software that will enable us all to build on each other’s work and perhaps benefit our discipline as a whole.

ACKNOWLEDGMENTS

One of the authors (TM) is funded by the National Institute for Health Research (NIHR) Collaborations for Leadership in Applied Health Research and Care (CLAHRC) Wessex. The views expressed in this publication are those of the author and not necessarily those of the National Health Service, the NIHR, or the Department of Health.

A AGENT-BASED INFECTION MODEL STRESS RECORD

<table>
<thead>
<tr>
<th>Section/Subsection</th>
<th>Item</th>
<th>Recommendation</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. Objectives</td>
<td>1.1</td>
<td>Explain the background and rationale for the model. <em>The purpose of the model is to study infectious disease spread for various population dynamics.</em></td>
</tr>
<tr>
<td></td>
<td>1.2</td>
<td>State the qualitative or quantitative system level outputs that emerge from agent interactions within the ABS. <em>The outputs of the model are the sizes of the infected, susceptible and recovered population. The output is recorded every five days (simulation time unit is day).</em></td>
</tr>
<tr>
<td></td>
<td>1.3</td>
<td>If the model has been used for experimentation, state the research questions that it was used to answer. <em>The experimentation aim is to demonstrate the deployment of Agent-Based Simulation in Science Gateways/Open Science.</em></td>
</tr>
<tr>
<td>2. Logic</td>
<td>2.1</td>
<td>Provide one or more of: state chart, process flow or equivalent diagrams to describe the basic logic of the base model to readers. Avoid complicated diagrams in the main text.</td>
</tr>
</tbody>
</table>
Base model logic 2.2  Give details of the base model logic. This could be text to explain the overview diagram along with extra details including ABS product and process patterns. Include details of all intermediate calculations.

The model starts an infection outbreak with an initial population of infected and susceptible agents. Infected agents move close to susceptible agents and infect them while susceptible agents move where the least infected agents are located. Infected and susceptible agents interact with each other every simulation time unit (day). Infected agents recover after a period of time and become recovered with a level of immunity. When an infected agent gets in touch with a susceptible agent, the susceptible agent becomes infected. When an infected agent gets in touch with a recovered agent, the recovered agent decreases its immunity. When the immunity level is 0, the recovered agent becomes susceptible and can be infected again. The outbreak occurs annually. When this happens, the population changes to reflect the initial conditions taking into account the population of the previous year.

Scenario logic 2.3  Give details of any difference in the model logic between the base case model and scenarios. This could be incorporated as text or, where differences are substantial, could be incorporated in the same manner as 2.1. N/A (only parameter sweep)

Algorithms 2.4  Provide further detail on any algorithms in the model that (for example) mimic complex or manual processes in the real world. N/A

Components 2.5 2.5.1. Environment
Describe the environment agents interact within, indicating its structure, and how it is generated.
Euclidean 2D space for free movement. Grid for neighbourhood definition. Network for infection connections

2.5.2. Agents
List all agents and agent groups within the simulation.
Initial population: \{Infected=20, Susceptible=1500, Recovered=0\}

**Infected**
Attributes: Location, Days infected:

**Logic**
01. Find where most susceptible are located
02. Move towards this grid location
03. If in contact with an agent{
05. If (contacted agent = susceptible){infect}
06. If (contacted agent = recovered){reduce immunity}
Describe all decision-making rules that agents follow in either algorithmic or equation form.

- The data that agents access (i.e. internal attributes or external information from the environment) and how it is used.
- **Internal distributions**
- The objectives agents seek to achieve.
- *Infected: move close to susceptible*  
  *Susceptible: move away from infected*
- The algorithms, optimisations, heuristics and rules that agents use to achieve objectives.
- *Infected: find where most susceptible are located*  
  *Susceptible: move where least infected are located*  
  - How agents work together within a group along with any rules for changes in group membership.
- *They do not work in groups*
- Predictions of future events and adaptive action.
- N/A

### 2.5.3. Interaction Topology
Describe how agents and agent groupings are connected with each other in the model define:

- with whom agents can interact,
- *Interacting agents: infected with susceptible and recovered*
- how recipients of interactions are selected
- *Random selection*
- what frequency interaction occurs.
- *Every simulation time unit*
- How agents handle and assign priorities to concurrent events
- *No priorities (random execution of actions scheduled for the same time unit)*

### 2.5.4 Entry / Exit
Where relevant, define how agents are created and destroyed in the model.

*All agents are created at initialization. They are not destroyed however they change state.*

### 3. Data

<table>
<thead>
<tr>
<th>Data sources</th>
<th>3.1</th>
<th>List and detail all data sources. Sources may include:</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td><em>This is a demo model with no real data.</em></td>
</tr>
</tbody>
</table>
3.2 List all input parameters in the model, providing a description of each parameter and the values used.

Model parameters:
- Initial population: \{Infected=20, Susceptible=1500, Recovered=0\}
- Recovery days: \{Uniform distribution (30,50)\}
- Immunity: \{Uniform distribution (5,10)\}

3.3 Provide details of any data manipulation or filtering that has taken place before its use in the simulation.

None.

3.4 Where data or knowledge of the real system is unavailable, state and justify the assumptions used to set input parameter values and distributions; agent interactions or behaviour; or model logic.

See above.

4. Experimentation

4.1 State if a warm-up period has been used, its length and the analysis method used to select it.

No warm-up period

State what if any initial agent and environmental conditions have been included.

Initial population: \{Infected=20, Susceptible=1500, Recovered=0\}

4.2 Detail the run length of the simulation model and time units.

20 years

4.3 State if the model is deterministic or stochastic.

Deterministic

5. Implementation

5.1 State the operating system and version and build number.

It can run in any OS, Repast Simphony 2.1, Java 7.5.1.

5.2 State the algorithm or package used to generate random samples within the software/programming language used.

Repast Random Helper.

5.3 If the ABS model has a time component, describe how time is modelled (e.g. fixed time steps or discrete-event).

Fixed time steps
Random execution of agent actions
Last priority for recording outputs
First priority for annual outbreak

5.4 State the model run time and specification of hardware used.

Runtime: 20 min
VM with all dependencies (repast libraries, model source code and scenario, java runtime)

All results and software can be found in the DOI Collection https://dx.doi.org/10.15169/sci-gaia:1457690398.43

REFERENCES


AUTHOR BIOGRAPHIES

SIMON J. E. TAYLOR is a full Professor and leader of the Modelling & Simulation Research Group in the Department of Computer Science, Brunel University London (https://tinyurl.com/ya5zjh8z). He leads major projects in industry and Africa. He a member of the ACM SIGSIM Steering Committee and founder of the Journal of Simulation. He has chaired several major conferences and his published over 150 articles. His email address is simon.taylor@brunel.ac.uk and his ORCID is orcid.org/0000-0001-8252-0189.

ANASTASIA ANAGNOSTOU is Research Fellow at the Department of Computer Science, Brunel University London and a member of the Modelling & Simulation Research Group. She holds a PhD in Hybrid Distributed Simulation, a MSc in Telemedicine and e-Health Systems and a BSc in Electronics Engineering. Her research interests are related to the application of modeling and simulation techniques in the Healthcare and Industry. Her email address is anastasia.anagnostou@brunel.ac.uk and her ORCID is orcid.org/0000-0003-3397-8307.

CHRISTINE CURRIE is Associate Professor of Operational Research in Mathematical Sciences at the University of Southampton, UK, where she also obtained her Ph.D. She is Editor-in-Chief for the Journal of Simulation. Her research interests include mathematical modelling of epidemics, Bayesian statistics, revenue management, variance reduction methods and optimization of simulation models. Her email address is christine.currie@soton.ac.uk and her ORCID is orcid.org/0000-0002-7016-3652.

THOMAS MONKS is funded by NIHR CLAHRC Wessex where he is Director of the Data Science Hub. He holds a BSc in Computer Science and Mathematics, MSc in Operational Research and PhD in Simulation Modelling. His research interest is applied simulation modelling and optimization in healthcare. His views do not necessarily reflect those of the NHS, NIHR, or Department of Health. His email address is thomas.monks@soton.ac.uk and his ORCID is orcid.org/0000-0002-7016-3652.

BHAKTI STEPHAN ONGGO is an Associate Professor of Data Analytics at Trinity Business School, Trinity College Dublin, The University of Dublin, Ireland. His research interests lie in the areas of predictive analytics using simulation (data-driven simulation, hybrid modelling, agent-based simulation, discrete-event simulation) with applications in operations and supply chain management (e.g. hospital, manufacturing, transportation) and social science (e.g. spread of perception). He is the associate editor for the Journal of Simulation.

MARTIN H KUNC is an Associate Professor of Management Science at Warwick Business School, University of Warwick. He holds a PhD in Decision Sciences from London Business School, UK. His research interests lie in system dynamics simulation modeling, especially in healthcare, strategic decision making processes and dynamics of competitive industries. His email address is martin.kunc@wbs.ac.uk.

STEWART ROBINSON is Dean and Professor of Management Science at Loughborough University, School of Business and Economics. Key areas of interest are conceptual modeling, model validation, output analysis and alternative simulation methods (discrete-event, system dynamics and agent based). Home page: www.stewartrobinson.co.uk.