Proceedings Paper:

Yin, C and McKay, A orcid.org/0000-0002-8187-4759 (2018) Introduction to Modeling and Simulation Techniques. In: Proceedings of ISCIIA 2018 and ITCA 2018. The 8th International Symposium on Computational Intelligence and Industrial Applications and The 12th China-Japan International Workshop on Information Technology and Control Applications, 02-06 Nov 2018, Tengzhou, China. .

Introduction to Modeling and Simulation Techniques

Chenggang Yin*1 and Alison McKay2

*1 Department of Mechanical Design and Manufacture, College of Engineering, China Agricultural University, Beijing, China
E-mail: cgyin@cau.edu.cn
2 School of Mechanical Engineering, University of Leeds, Leeds, UK
E-mail: A.McKay@leeds.ac.uk

Abstract: Modeling and simulation techniques are becoming an important research method for investigating operational and organizational systems. Many literatures report different aspects and views of modeling and simulation but there is little literature that covers a full cycle of modeling and simulation, including both model design & development and model verification & validation, for use in industrial product development systems. This paper introduces modeling and simulation concepts, methods and tools, and discusses approaches that can be used for model verification and validation. A modeling and simulation procedure, designed for use in understanding industrial product development systems, is introduced that accommodates both model creation and verification & validation. The overall goal of the research is to bridge the gap between model design & development and model verification & validation in a modeling and simulation procedure which, as a whole, is essential for the application of modeling and simulation techniques to understand any real-world system.

Keywords: Modeling and Simulation, Modeling and Simulation Procedure, Model Verification and Validation, Agent-Based Simulation (ABS), Discrete-Event Simulation (DES)

1. BACKGROUND

Modeling and simulation techniques are being widely applied in organizational and operational systems, in addition to their success in physical system design, manufacture, analysis and improvement. Modeling and simulation involves a process of designing a model of a real-world or anticipated system such as a design concept, then conducting experiments with the model for the purposes of understanding the performance of the system under different operating conditions and evaluating alternative management strategies and decision-making processes [1, 2]. Modeling and simulation technology is increasingly considered to be a third scientific research methodology, in addition to the traditional deductive and inductive approaches [3, 4].

Many researchers have contributed to modeling and simulation technologies. For example, Shannon gave a definition of simulation and predictive modeling [1], Klingstam and Gullander introduced the discrete-event simulation (DES) method [5], and Macal and North proposed an agent-based simulation (ABS) tutorial [4]. Siebers et. al. presented advantages and disadvantages between DES and ABS, Sargent considered different approaches for simulation model verification and validation [7], Hughes et. al. reported modeling and simulation applications to organizational systems [8], and Abar et. al. provided a review of agent-based simulation methods and development [9].

Many researchers work on modeling and simulation methods, procedures, strategies and applications in different scientific research areas. However, there is little literature that covers a full cycle of modeling and simulation, including both model design & development and model verification & validation, for use in industrial product development systems. As a result, it can be difficult for practitioners to determine the validity of given simulation models and so the reliability of results from simulation experiments.

This paper introduces a procedure (see Section 5) that covers a full cycle of modeling and simulation, including both model design & development and model verification & validation, for use in industrial product development systems. The procedure was evaluated through application to a real-world new product development process case study as part of a PhD research project [48]. The procedure is based on modeling and simulation concepts discussed in Section 2; and modeling and simulation domains and methods that are introduced in Sections 3 and 4 respectively. Section 6 considers model verification and validation methods in more details and Section 7 concludes the paper.

2. MODELING AND SIMULATION CONCEPTS

Two definitions of modeling and simulation were used as the basis of this work. Modeling and simulation is defined by Bratley et. al. as a process of driving a model of a system with suitable inputs and observing the correspondingly outputs [10] and by Shannon as the process of designing a model of a conceptual system and using it to conduct experiments for the purpose of understanding the performance of the system and/or evaluating alternative management strategies and decision-making processes using simulation results [1, 2].

The purpose of modeling and simulation includes performance assessment, proof, prediction, discovery, training, entertainment and education [3]. Simulation techniques are applied in various research fields including computer systems, manufacturing processes, societal systems, business organizations, government systems, ecology environment systems, and other complex processes and systems [1, 2]. Modeling and simulation methods have also been applied to interdisciplinary research fields such as design system decision-making mechanisms [11, 12], the management of integrated product teams [13], new product development processes [14, 15, 16], and organizational management [8]. Application of modeling and simulation methods to understand the performance of complex socio-technical systems is becoming a promising research area [3, 8].

3. MODELING AND SIMULATION DOMAINS

In engineering, modeling and simulation techniques are applied to two distinct types of system: physical mechanisms whose performance is governed by the laws of physics and process-based systems whose performance are governed by human, group and organizational behaviors.

3.1. Mechanism Simulation

Mechanism simulation relates to the simulation of physical systems, through which movement, degree of freedoms (DOFs), velocities and component stresses can be simulated and analyzed for whole machine optimization. Fig. 1 displays an example kinematic simulation of 3D CAD model.

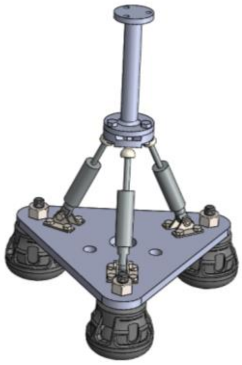

Fig. 1 Mechanism simulation

Fig. 1 shows an assembly of a spatial linkage mechanism that includes different mechanical parts. Simulation purposes are specified, for example, to examine whether it can produce three spatial degrees of freedoms (DOFs), and the strength of the materials is sufficient when external force applies.

3.2. Process and System Simulation

Process and system simulation relates to the simulation of different organizational and operational systems, including but not limited to manufacturing systems [17], industrial production processes, business service systems [3], complex problem-solving process [18], business organizations [19], socio-technical systems [8], human systems [20], and automotive assembly systems [21]. Fig. 2 gives an example of a new product development process simulation case study conducted by the authors.

In Fig. 2, the simulation model is developed to mimic a new product development process that includes four work teams, i.e. preliminary design, detail design, manufacturing and service. The purpose of the simulation was to understand the operational processes and find out which teams consume additional time resources for design iteration across different stages in the process with a view to identifying improved management strategies, with an overall goal to shorten product development duration and so improve time-to-market performance. The focus of the rest of this paper is on process and system modeling and simulation.

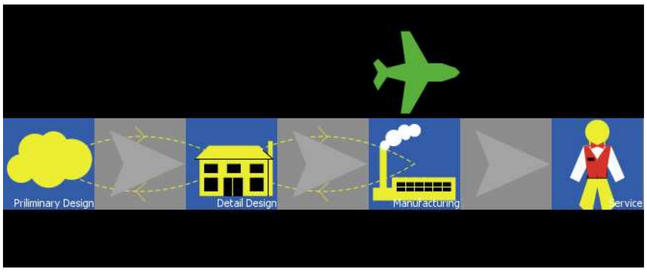

Fig. 2 Process and system simulation

4. MODELING AND SIMULATION METHODS

Two common simulation methods applied in operational management systems are agent-based simulation (ABS) [6] and discrete-event simulation (DES) [22]. These can be used in conjunction with other simulation methods such as mathematical simulation and Monte Carlo simulation.

4.1. Agent-Based Simulation (ABS)

Agent-based simulation (ABS) is a fast-developing modeling and simulation method [9, 23, 24, 25] that can be used to model and simulate industrial process and complex scientific systems [26, 27]. Agent-based simulation builds up its models using a bottom-up architecture [4, 23]. It comprises a series of autonomous agents that act and interact with each other complying with defined simulation specifications in a simulation world. Key characteristics of agent-based simulation are as follows [15, 23]:

- bottom-up modeling architecture;
- focus on modeling individual agents and interactions between them;
- a decentralized simulation model architecture, i.e., each agent has its own thread of control;
- The modeled system performance is not defined in the simulation model but emerges from the autonomous agents' actions, interactions and decision-makings;
- queueing issues are not defined;
- model inputs are often based on theories and subjective data related to the agents' behaviors; and
- individual agents can use their own initiative and make decisions that influence the behavior of the overall system.

Within agent-based simulation models, autonomous agents act and interact with each other complying with defined simulation rules in a simulation world. Micro-level individual agent's actions and behaviors influence and determine macro-level system performance which, as a whole, can be observed and analyzed by users of the simulation model [23].

Agent-based simulation is becoming an important problem-solving approach for many situations where overall system behaviors emerge from micro-level behaviors [9, 27, 28]. There are many for agent-based simulation software tools, each suited to particular kinds of application. Agent-based simulation tools include, but are not limited to: NetLogo, Spread sheet, Repast, Starlogo, Swarm, Matlab, Mathematica, Anylogic, and others [6, 8, 9, 23, 26, 29, 30].

4.2. Discrete-Event Simulation (DES)

Discrete-event simulation (DES) is a more mature simulation method than agent-based simulation [6]. Discrete-event simulation is one way to build up models in a top-down architecture and observe time-based behaviors within a system. Formal methods have been developed to construct discrete event simulation models and ensure that the models are credible [6]. Arena and Witness are two examples of discrete-event simulation tools [5, 31].Primary characteristics of discrete-event simulation are as follows [6]:

- top-down modeling approach;
- focus on modeling overall system processes in detail;
- a centralized simulation system architecture, i.e., a given simulation has one thread of control;
- the modeled system performance is related to the defined system process;
- the identification of queues is a key consideration in overall system performance;
- model inputs are often based on objective data, e.g., that has been collected from the system that is being modeled; and
- Entities in the simulation model are process steps related to other steps but with no capacity to act independently; the performance of the overall system depends on relationships between process steps.

5. MODELING AND SIMULATION PROCEDURES

Modeling and simulation procedures guides modeling and simulation activities, including creating a problem statement, conceptual model development, simulation model construction, and model verification & validation. Specific procedures used to simulate real-world problems may vary for a range of reasons, such as differences in problem statement, purpose of simulation experiments, experimenters' preferences, and limitation of the simulation technologies that are used.

5.1. Modeling and Simulation Processes

Contributions to modeling and simulation process development include [1, 28, 32, 33]. For example, Shannon's simulation procedure includes the following steps [1]:

- System Definition
- Model Formulation
- Data Preparation
- Model Translation
- Validation
- Strategic Planning
- Tactical Planning
- Experimentation
- Interpretation
- Implementation
- Documentation

Seila proposed another modeling and simulation process [33], which includes thirteen steps:

- Problem Statement and Objectives
- Systems Analysis
- Analysis of Input Distribution
- Model Building
- Design and Coding of the Simulation Program
- Verification of the Simulation Program
- Output Data Analysis Design
- Validation of the Model
- Experimental Design
- Making Production Runs
- Statistical Analysis of Data
- Implementation
- Final Documentation

5.2. Modeling and Simulation Procedure

Fig. 3 shows a simulation procedure designed by the authors, to guide research activities and experiments in a real-world problem solving case study. The process was evaluated through application to a case study where the research intent was to explore the time-related performance of a new product development process, with a view to identifying time resource used by work teams in the process and proposing improved management strategies that would reduce product development cycle times. The thirteen-step procedure, shown in Fig. 3, and each step is described in the remainder of this section.

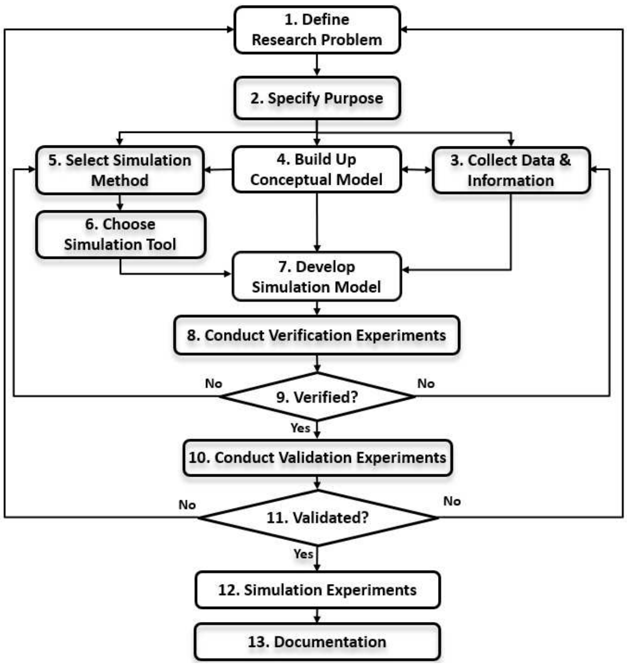

Fig. 3 Modeling and simulation procedure

1. **Define research problem:** research interests from case study owners are elaborated, the real-world problem is identified, and expectations of the research outcomes are agreed.
2. **Specify purpose:** the purpose of the simulation experiments, in the form of an aim & objectives, is specified.

3. **Collect data & information:** the data and information needed for the definition of both conceptual and simulation models is specified and collected as input data for the simulation experiment. It should be noted that this is typically an iterative negotiation process between the research team and case study owners because the necessary data needs to exist in an appropriate form and be accessible. If it is not then case study owners might work with the research team to develop a synthetic data set.
4. **Build up conceptual model:** a conceptual model is defined and built up with respect to specified research purpose using data and information collected, in order to represent relationships that are relevant to the research problem.
5. **Select simulation method:** a modeling and simulation method is selected to represent the defined research problem. Selection of the simulation method includes consideration of both suitability and feasibility.
6. **Choose simulation tool:** the software tool in which the simulation model will be implemented is selected. This selection process includes consideration of both tool availability and adaptability.
7. **Develop simulation model:** a computer-based simulation model of the conceptual model is developed using the selected simulation method and tool.
8. **Conduct verification experiments:** verification experiments are conducted with the simulation model, with a focus on checking whether the simulation model gives reliable and anticipated outputs for given inputs in scenarios with which the case study owners are familiar.
9. **Verify the simulation model:** simulation results from verification experiments are reviewed; the simulation model and results are verified against specified verification methods and indicators. If necessary, steps 3, 4, 5, 6, 7 and 8 may be revisited. By addressing comments, feedbacks, and suggestions from different perspectives, the simulation model is improved and upgraded for the next stage.
10. **Conduct validation experiments:** validation experiments are conducted using revised simulation model. Validation experiments are to check whether the simulation model possesses sufficient accuracy to represent and then address the research problem, with respect to the specified research purpose.
11. **Validate the simulation model:** results from the validation experiments are validated against specified validation methods and indicators. If necessary, earlier steps may be revisited.
12. **Simulation experiments:** simulation experiments are conducted to simulate real-world operational scenarios. Simulation results are analyzed and discussed. Potential management solutions are considered to address the specified research problems.
13. **Documentation:** instructions and documents supporting the simulation model and simulation experiments are developed, e.g. how to operate the simulation model, how to set input data values, and how to analyze model results. This step is necessary for other users or clients to understand, modify, or further improve the simulation model if necessary. It also enhances confidence for users applying the model to solve the real-world problems. In the case study used to evaluate this process, a user manual for operating the simulation model was developed.

6. MODEL VERIFICATION AND VALIDATION

The purpose of model verification and validation is to make the simulation model meaningful in a real-world context. For this reason, the modeling and simulation procedure includes model verification and validation, in addition to model design and development. Fig. 3 gives an example of full vision of a model verification and validation architecture. Model verification and validation activities include validation of the simulation model with respect to the real-world situation and the conceptual model.

6.1. Model Verification and Validation Concepts

Model verification concerns the identification and removal of errors in the simulation model by comparing simulation results from the model to analytical solutions from the real-world situation [34]. In this way, the model verification process deals with the mathematical relationships and simulation specifications associated with the model [35, 36]. Model verification ensures that the model is as complete and correct as is necessary to give a sufficiently accurate representation of the real-world situation [37, 38]. In this way, model validation ensures that the simulation model is useful for real-world problem-solving [35]. Model validation processes are concerned with quantifying the accuracy of the model by comparing simulation results to experimental or operational outcomes in the real world [36]. Contributors to model verification and validation knowledge domains include [7, 39, 40, 41, 42, 43, 44, 45].

6.2. Verification and Validation Architecture

Fig. 4 illustrates a model verification and validation architecture for the implementation of relevant activities in Fig. 3.

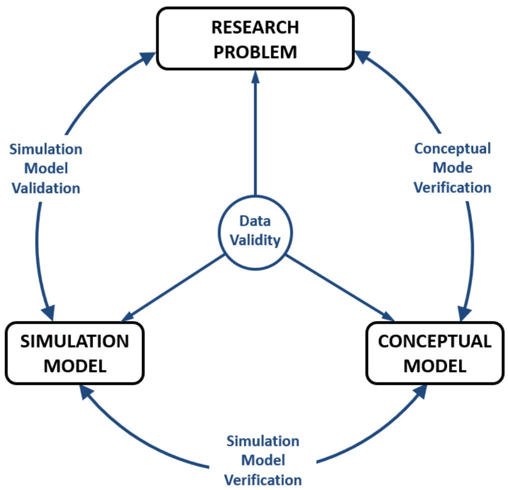

Fig. 4 Model verification and validation architecture

The oblongs in Fig. 4 represent outcomes from three primary steps in Fig. 3: the definition of the research problem from the research problem definition (Step 1), the conceptual model (from Step 4) and the simulation model (from Step 7).

As shown in Fig. 4, three verification and validation activities are needed. Firstly, conceptual model verification ensures that the conceptual model is an accurate representation of the research problem in real-world situation. Secondly, simulation model verification ensures that the computer-based simulation model is a sufficiently accurate implementation of the concept model. And finally, simulation model validation conducts a series of simulation experiments which focus on checking the model's efficiency and accuracy with respect to specific research purpose. In addition, at the center of the diagram in Fig. 4, all data used in all aspects of both model design & development and model verification & validation needs to be validated.

6.3. Model Verification and Validation Strategies

Researchers have developed different model verification and validation strategies with their experience in either academic research or industry. Contributions to this knowledge domain include [7, 36, 39, 41, 46, 47]. There are four primary strategies used to verify and validate simulation models [7]:

- **Self-Validation:** The simulation model development team itself makes the decision as to whether a simulation model is valid or not;
- **Co-Validation:** The simulation team involves model users within model development process; the model validation process is integrated within the model development process;
- **Independent Validation:** An independent third party is employed to decide whether a simulation model is valid or not; and
- **Scoring Validation:** A scoring model is used to determine whether a simulation model is valid or not.

Each strategy has distinct features which means that different strategies are suitable for different real-world situations and simulation purposes. Detailed explanation of model verification and validation strategies is available in references listed above.

6.4. Model Verification and Validation Methods

There are many model verification and validation methods developed for specific simulation situations. Contributions to the model verification and validation methods community include [7, 39, 40, 41, 42, 43, 44, 45]. A series of model verification and validation methods are listed as follows.

- Animation Validation
- Model to Model Validation
- Event Validation
- Extreme Condition Validation
- Face Validation
- Historical Data Validation
- Operational Graphics Validation
- Sensitivity Analysis Validation
- Predictive Validation
- Traces Validation
- Turing Test Validation
- Game Validation

Different model verification and validation methods have different advantages and limitations, which means, again, that different methods are suitable for different real-world problem situations and research purposes. Regarding model verification and validation method selection, more information can be found in publications cited above.

7. CONCLUSIONS

Modeling and simulation techniques are becoming an important research method for investigating operational and organizational systems. Existing literatures report different views and aspects of modeling and simulation techniques with specified interests, but there is limited literature that presents a full vision of modeling and simulation in a procedure suitable for engineering design applications. The contribution of this paper is to bridge the gap between model design and development, and model verification and validation by providing such a modeling and simulation procedure.

A modeling and simulation procedure was demonstrated with focus on a real-world problem-solving case study. The procedure accommodates model verification & validation activities into model design & development process which, as a whole, forms a full cycle of modeling and simulation.

This paper discussed modeling and simulation concepts, domains, methods and processes. Two common modeling and simulation methods were discussed, i.e. agent-based simulation (ABS) and discrete-event simulation (DES). In addition, model verification and validation concepts, strategies and methods were evaluated. The research is expected to be helpful for researchers and practitioners working in modeling and simulation fields.

ACKNOWLEDGEMENTS

The research is supported by China 13th Five-Year National Key Research and Development Plan (Project No.: 2017YFD0701102-1). The work reported in this paper was part of a PhD project that was co-supervised by Professor Chris W. Clegg (deceased).

REFERENCES:

[1] R. E. Shannon, Simulation: An overview, Winter Simulation Conference, Arlington, Virginia, USA, 1983.

[2] R. E. Shannon, Introduction to simulation, Winter Simulation Conference, Arlington, Virginia, USA, 1992.

[3] R. Axelrod, Advancing the Art of Simulation in the Social Sciences, Japanese Journal for Management Information System, Special Issue on Agent-Based Modeling, 2003, 12(3).

[4] C. M. Macal and M. J. North, Agent-based modeling and simulation: Desktop ABMS, Winter Simulation Conference, 2007.

[5] P. Klingstam and P. Gullander, Overview of simulation tools for computer-aided production engineering, Computers in Industry, 1999, 38(2), pp. 173-186.

[6] P. O. Siebers, C. M. Macal, J. Garnett, D. Buxton, and M. Pidd, Discrete-event simulation is dead, long live agent-based simulation! Journal of Simulation, 2010, 4(3), pp. 204-210.

[7] R. G. Sargent, Verification and validation of simulation models, Journal of Simulation, 2013, 7(1), pp. 12-24.

[8] H. P. N. Hughes, C. W. Clegg, M. A. Robinson, and R. M. Crowder, Agent-based modeling and simulation: The potential contribution to organizational psychology, Journal of Occupational and Organizational Psychology, 2012, 85(3), pp. 487-502.

[9] S. Abar, K. G. Theodoropoulos, P. Lemarinier, and M. P. G. O'Hare, Agent Based Modeling and Simulation tools: A review of the state-of-art software, Computer Science Review, 2017.

[10] P. Bratley, B. L. Fox, and L. E. Schrage, A guide to simulation (2nd Ed.), New York, Springer, 1987.

[11] H. M. E. Abdelsalam and H. P. Bao, A simulation-based optimization framework for product development cycle time reduction, Engineering Management, 2006, 53(1), pp. 69-85.

[12] L. T. T. Pesonen, S. J. Salminen, J.-P. Ylen, and P. Riihimaki, Dynamic simulation of product process, Simulation Modeling Practice and Theory, 2008, 16(8), pp. 1091-1102.

[13] Y. W. Sim, R. Crowder, M. Robinson, and H. Hughes, An Agent-based approach to modeling integrated product teams undertaking a design activity, ASME 2009 International Design Engineering Technical Conferences and Computers and Information in Engineering Conference, San Diago, CA, USA, 2009.

[14] N. Bhuiyan, D. Gerwin, and V. Thomson, Simulation of the New Product Development Process for Performance Improvement, Management Science, 2004, 50(12), pp. 1690-1703.

[15] R. Garcia, Uses of Agent-Based Modeling in Innovation/New Product Development Research*, Journal of Product Innovation Management, 2005, 22(5), pp. 380-398.

[16] D. C. Wynn, C. M. Eckert, and P. J. Clarkson, Modeling interation in engineering design, International conference on engineering design, Paris, 2007.

[17] J. Barbosa and P. Leitao, Simulation of Multi-agent Manufacturing Systems using Agent-based Modeling Platforms, the 9th IEEE International Conference on Industrial Informatics, 2011.

[18] M. Pereda and J. M. Zamarreno, Agent-based modeling of an activated sludge process in a batch reactor, the 19th Mediterranean Conference on Control & Automation, 2011.

[19] O. Nicolae and G. Wagner, Modeling and simulating organisations, the 7th International Workshop on Enterprise & Organizational Modeling and Simulation, London, 2011.

[20] E. Bonabeau, Agent-based modeling: methods and techniques for simulation human systems, the National Academy of Sciences, CA, 2002.

[21] D. Kibira and C. R. McLean, Generic simulation of automotive assembly for interoperability testing, Winter Simulation Conference, 2007.

[22] S.-H. Cho and S. Eppinger, Product development process modeling using advanced simulation, 2001.

[23] C. M. Macal and M. J. North, Tutorial on agent-based modeling and simulation, Journal of Simulation, 2010, 4(3), pp. 151-162.

[24] A. Garro and W. Russo, easyABMS: A domain-expert oriented methodology for agent-based modeling and simulation, Simulation Modeling Practice and Theory, 2010, 18(10), pp. 1453-1467.

[25] C. Macal and M. North, Introductory tutorial: agent-based modeling and simulation, Winter Simulation Conference, Savannah, Georgia, 2014.

[26] W. N. Robinson and Y. Ding, A survey of customization support in agent-based business process simulation tools, ACM Transactions on Modeling and Computer Simulation, 2010, 20(3), pp. 1-29.

[27] N. Seekhao, C. Shung, J. JaJa, L. Mongeau, and N. Y. K. Li-Jessen, Real-Time Agent-Based Modeling Simulation with in-situ Visualization of Complex Biological Systems: A Case Study on Vocal Fold Inflammation and Healing, IEEE International Symposium on Parallel & Distributed Processing, Workshops and PhD Forum, 2016, pp. 463-472.

[28] J. Banks, Introduction to simulation, Winter Simulation Conference, Phoenix, Arizona, United States, 1999.

[29] E. Sklar, Software review: NetLogo, a multi-agent simulation environment, Artificial Life, 2007, 13(3), pp. 303-311.

[30] C.-G. Yin and Y.-S. Ma, Parametric feature constraint modeling and mapping in product development, Advanced Engineering Informatics, 2012, 26(3), pp. 539-552.

[31] W. D. Kelton, R. P. Sadowski, and D. A. Sadowski, Simulation with Arena, McGraw-Hill, Inc., 2002.

[32] C. D. Pegden, R.E. Shannon, and R.P. Sadowski, Introduction to Simulation using SIMAN (Second Edition), New York: McGraw-Hill, 1995.

[33] A. F. Seila, Introduction to simulation, Winter Simulation Conference, 1995.

[34] A. M. Law, Simulation modeling and analysis (4th Edition), New York: McGraw-Hill, 2007.

[35] C. M. Macal, Model verification and validation, Workshop on Threat anticipation: Social science methods and models, University of Chicago and Argonne National Laboraory, 2005.

[36] B. H. Thacker, S. W. Doebling, F. M. Hemez, M. C. Anderson, J. E. Pepin, and E. A. Rodriguez, Concepts of Model Verification and Validation, 2004.

[37] O. Balci, Verification validation and accreditation of simulation models, Winter simulation, Atlanta, Georgia, USA, 1997.

[38] D. S. Riha, B. H. Thacker, J. B. Pleming, J. D. Walker, S. A. Mullin, et al., Verification and validation for a penetration model using a deterministic and probabilistic design tool. International Journal of Impact Engineering, 2006, 33(1–12), pp. 681-690.

[39] J. S., II. Carson, Model verification and validation, Winter Simulation Conference, 2002.

[40] C. M. Macal and M. J. North, Validation of an agent-based model of deregulated electric power markets, North American Computational Social and Organization Science Conference, 2005.

[41] S. Robinson, Simulation model verification and validation: increasing the users' confidence, the 29th Winter Simulation Conference, Atlanta, Georgia, USA, 1997.

[42] X. Xiang, R. Kennedy, G. Madey, and S. Cabaniss, Verification and Validation of Agent-based Scientific Simulation Models, ADS, 2005.

[43] N. Gilbert, Model building and Validation, Siumulation Innovation: a Node, University of Surry, England, 2010.

[44] O. Balci, Golden rules of verification, validation, testing, and certification of modeling and simulation applications, SCS Modeling & Simulation Magazine, 2010.

[45] O. Balci, A life cycle for modeling and simulation, Journal of Simulation, 2012, 88(7), pp. 870-883.

[46] O. Balci, Validation, verification, and testing techniques throughout the life cycle of a simulation study, Annals of Operations Research, 1994, 53(1), pp. 121-173.

[47] J. Banks, J. S. Carson, B. L. Nelson, and D. M. Nicol, Discrete-event system simulation (5th Ed.), NJ: Upper Saddle River, 2010.

[48] C.-G. Yin, Simulating vicious circles in new product introduction systems, PhD thesis, University of Leeds, Leeds, UK, 2014

AUTHOR BIOGRAPHIES

Chenggang Yin is a Lecturer in Department of Mechancial Design and Manufacture, China Agricultural University. He holes a PhD in Mechanical Engineering at University of Leeds, UK. He obtained M.Eng at Beijing Institute of Technology. He worked as a research fellow (internal team leader) for H2020 RiserSure project at London South Bank Innovation Centre (LSBIC) in TWI Ltd between 2016 and 2017. He worked as a project engineer at InnoTecUK Ltd from 2014 to 2016. He has been a visiting scholar at University of Alberta, Canada, between 2009 and 2010. His research interests include product design and development, modeling and simualtion, agent-based simulaiton, complex design system, decision-making mechanism, orgnizational behavior, and others.

Alison McKay is Professor of Design Systems at the University of Leeds and director of the Leeds Socio-Technical Centre. She holds a PhD in Mechanical Engineering. Her research centres on socio-technical aspects of engineering design systems and the networks of organisations that both develop and deliver products to market, and support them through life to disposal or reuse. The focus of her personal research lies in the establishment of systematic and, where possible, well-founded underpinnings for such systems, in particular, for the definition of product data.