Bergmann, Sören; Strassburger, Steffen :

Challenges for the Automatic Generation of Simulation Models for Production Systems

Zuerst erschienen in:
2010 International Simulation Multiconference / Summer Computer Simulation Conference, SCSC ; (Ottawa) : 2010.07.11-14. - [S.l.]: Omni Press, 2010. - 1 CD-ROM. - ISBN 1-565-55344-6. - S. 545-549.

Challenges for the Automatic Generation of Simulation Models for Production Systems

Sören Bergmann, Steffen Strassburger
Ilmenau University of Technology
School of Economic Sciences
P.O. Box 100 565, D-98684 Ilmenau, Germany
Email: soeren.bergmann@tu-ilmenau.de / steffen.strassburger@tu-ilmenau.de

Keywords: Discrete event simulation, automatic model generation, production systems, integration

Abstract

This paper is intended as an introduction of the challenges that exist in the area of automatic simulation model generation in the production and logistics context. As a work-in-progress paper, it firstly analyzes and classifies previous work; it then introduces the most relevant challenges and lastly presents potential solutions currently being investigated by a PhD thesis.

1. MOTIVATION

Simulation is used within many different disciplines and application areas. In the area of production and logistics, simulation is a well accepted tool for the planning, evaluation and monitoring of relevant processes. It is applied to ensure the feasibility of planning concepts, to discover rationalization possibilities and to assist in decision making. A wide variety of commercial simulation systems mostly based on discrete-event simulation paradigms exists in the area of production and logistics.

Considering the lifecycle of production and logistic systems, simulation is traditionally applied in both the planning phase and the operation phase. In the planning phase, simulation supports the planning and dimensioning of production systems, the design of process alternatives as well as the design of control strategies. In the operation phase, simulation is used in the context of simulation based production control, as an early-warning-system [Hotz et. al 2006], and, more generally, as a tool for visualisation of complex processes to assist in management information systems and in decision making.

More recently, the usage of simulation in the context of virtual commissioning as “emulation” for the real system has received an increased interest in production and logistics [Boer and Saanen 2008]. Here, it is used to test real control software and hardware.

In any of these application contexts of simulation it is essential to adequately model reality in a simulation model in a way that allows sufficiently exact predictions about the real system. The quality of the simulation based predictions directly depends on the quality of the model. The modelling process for achieving high quality models which are verified and validated is time consuming and usually requires a simulation expert.

Moreover, the entire simulation technology is a very interdisciplinary technology which requires expertise in different knowledge areas, including computer science, economic sciences, as well as mechanical and industrial engineering and statistics.

The latter often constitutes a problem for the application of simulation in production and logistics, especially in smaller and medium sized enterprises. The benefit that can be achieved by simulation strongly depends on the capabilities of the modelling simulation expert.

In this context [Fowler and Rose 2004] have discussed future challenges for modelling and simulation of complex production systems. Among others, they identified the reduction of the time and effort for simulation studies as well as the integration of simulation with the real production as future research areas.

2. AUTOMATIC MODEL GENERATION

Given these challenges, approaches to automatically generate simulation models seem to be very appealing. In such approaches of automatic (or semi-automatic) model generation a simulation model is not created manually using the modelling tools of the chosen simulator, rather it is generated from external data sources using interfaces of the simulator and algorithms for creating the model. This is often also referred to as “data-driven model generation” [Eckardt 2002]. The promise of such approaches is that they, if successful, can reduce the amount of time needed to create a simulation model as well as the expertise needed for creating and conducting simulations.

There is a wide variety of potentially relevant external data sources and IT systems (Figure 1).

The relevant data of such sources can be roughly classified into

- technical data describing the topology of a production system as well as its components,

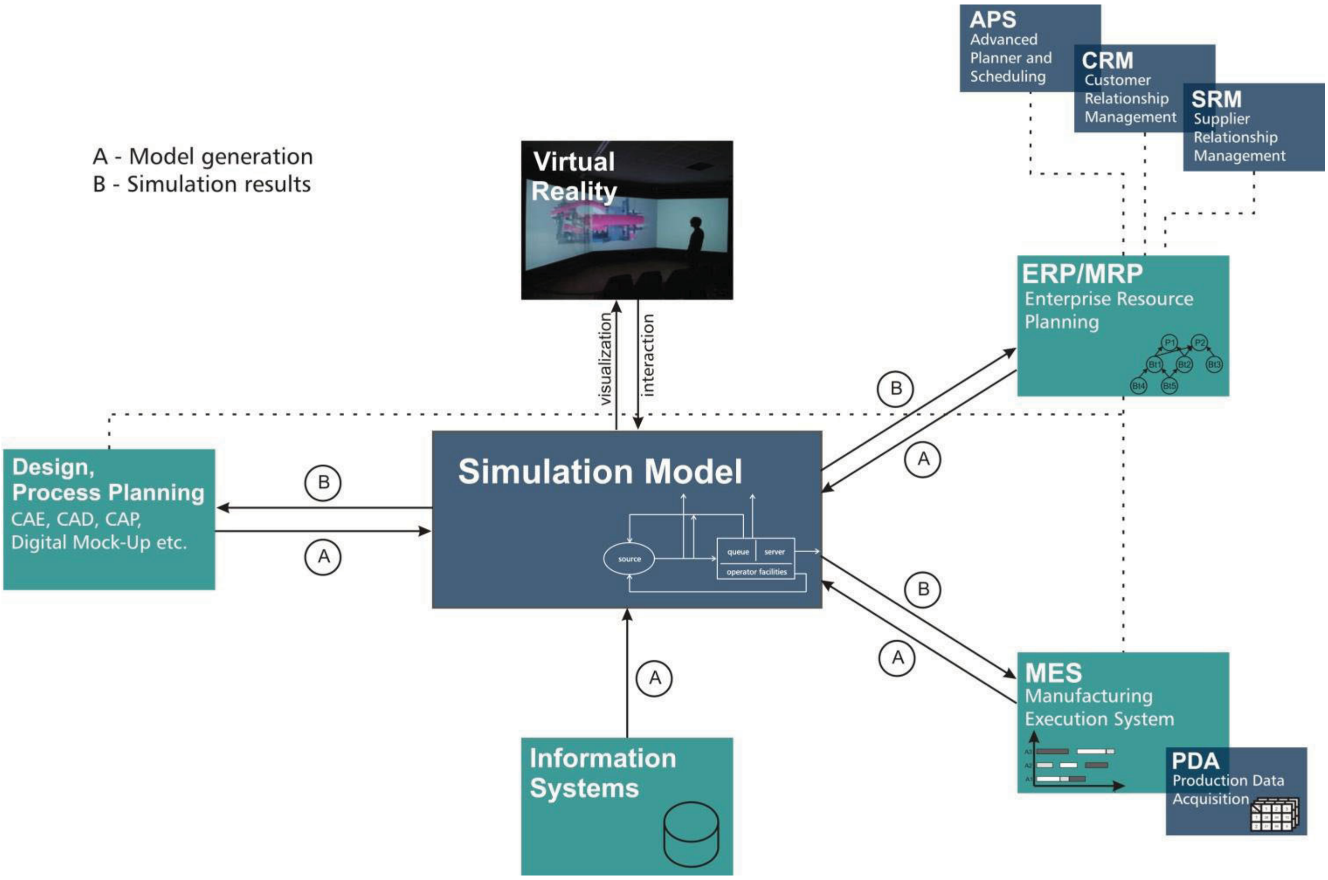

Figure 1: Relevant data sources for automatic model generation approaches

- organizational data defining the labor schedule and the process organization (including production control), information flow and resource allocation, and
- system load data consisting of real or simulated order and product data.

2.1. Related Work

In literature, several different approaches for semi-automatic model generation are discussed. Following [Eckardt 2002] and [Gmilkowsky et al. 1998] they can be classified into the following main categories:

1) Parametric approaches: Models are generated based on existing simulation building blocks stored in simulation libraries, which are selected and configured based on parameters.
2) Structural approaches: model generation is based on data describing the structure of a system, typically in the form of factory layout data from relevant CAD-systems [Lorenz and Schulze 1995]
3) Hybrid-knowledge-based approaches: These approaches combine artificial intelligence methods (expert systems, neuronal nets) with both of the above approaches.

Stimulated by digital factory initiatives simulation model generation has recently received a tremendous upturn in the automotive industry. Several German car manufacturers are seriously experimenting with its practical use.

Their approaches can be strictly distinguished into either supporting the planning phase [Wurdig and Wacker 2008], [Rooks 2009], or the operational phase of a factory [Splanemann 1995], [Reinhart and Selke 2002], [Selke 2004], [Jensen 2007].

International publications can be classified accordingly: [Randell and Bolmsjö 2001] focus on the planning phase and [Kronberger et al. 2006] focus on ERP integration aspects during the operational phase,

Each of the cited references focused on individual subproblems within simulation model generation, including the integration of simulation with other IT systems, the definition of neutral simulation data formats, the interpretation of control strategies, and others.

The general observation that can be made regarding all of these approaches is a lack of universal validity of the approaches as well as the level of automatism that they can truly reach. Also, it is questionable why all the approaches are limited to only one of the life cycle phases of a factory.

2.2. Challenges for Automatic Model Generation

Given these finding, we can ask ourselves, what the big challenges are for the automatic generation of simulation models. First of all, universal validity of a model generation approach may sound like a "grand challenge", but it certainly is a rather academic one. For practical applications, solutions for automatic model generation within a certain application domain or for a specific scenario are much more viable and can solve real-life problems while still imposing significant challenges which must be addressed.

These challenges include the following problems:

- Incomplete data in external systems

In the planning phase data of the intended system may very likely be incomplete or have a rather rough level of detail. Still, it may be desirable to conduct simulations very early during the planning phase to get an impression how the planned system may behave. Detailed information on control strategies may not yet be available at all.
In the operational phase, structural data about the production system may be available (e.g. in ERP-systems), but detailed data from the planning phase may not be available (see [Jensen 2007] for practical examples).
Furthermore some information needed for the simulation (e.g. probability distributions of breakdown times) may not be captured in the intended source systems at all.

- Generation of dynamic / complex behaviour

This challenge describes a common problem of all known model generation approaches: How can I deal with missing information regarding the dynamic behaviour of my system? The art of simulation model generation comes down to how to best capture and describe this dynamics. Automatic model generation approaches often fall short of appropriately generating this behaviour realistically. This can be due to simply missing information, e.g., if buffering or control strategies (FIFO, LIFO, ...) are simply not modelled in the source systems, or attributed to the fact that the behaviour can be so complex that only algorithmic descriptions can capture it correctly. In the latter case the simulation system's modelling language is often the only tool which has the expressiveness of capturing it and automatic model generation approaches must fall short of supporting/generating behaviour of this complexity.

- Support of cyclic approaches involving multiple model generations cycles

The level of automatism in many model generation approaches is often limited to a "semi"-automatic model generation. Often, a model which has a completeness of 80% can be generated. After that the simulation expert has to add certain model details, behavioural descriptions, experimentation parameters and the like. This for itself does not necessarily constitute a problem. But what happens when the original data in the external (planning) system changes? The model generation has to be started over again. It is therefore essential to come up with incremental model generation approaches which allow the model details which have been manually added by the simulation expert to survive in such cyclic model generation scenarios.

- Support of multiple life cycle phases of the production system

Model reuse is highly desirable, especially after the planning phase of a production system has resulted in a very detailed, highly realistic model of the system being built. In today's industrial reality these models are often discarded although they could be very beneficial for supporting the operation of the production system. The challenge here is how models of the planning phase can be adapted to work in the operational phase. Furthermore, models capable of learning and adapting to changes in the real systems are required, especially during the operational phase. This is due to the natural evolvement of the real system which often goes unnoticed by the planning or controlling department: machines can wear out; personnel can adapt to manual tasks and increase performance over time, etc. Without possibilities to (automatically) reflect these modifications into the simulation model of the operational production system the model becomes outdated and delivers inaccurate predictions.

2.3. Research Work in Progress

To address as many of the stated challenges as possible, our research tries to establish a methodology and framework for simulation model generation based on a close integration of simulation with the IT landscape of companies. The methodology further involves the continuous improvement of the quality of the generated simulation model based on current (online) data obtained from the real system. Therefore this approach can be classified as hybrid concerning its support for both the planning and the operational phase of a production system.
During the simulation model generation we focus on mechanisms to support automatic testing and adaptability. It is an important criterion of our framework to support adaptability of the generated models. We want to ensure that

generated models have the appropriate hooks and mechanisms for supporting automatic validation and adaptation based on data observed from the real system. A model shall be able to validate itself based on these observations and, if certain thresholds are exceeded, it shall implement mechanisms to adapt intended model parameters to the new circumstances. With that we can ensure that we always have an up-to-date model of the real operational production system which can serve purposes of decision support and forecasting.

The intended automatic validation resembles the basic idea of model calibration described in [Banks et al., pp. 361ff], but adds methodically to it, as it is not applied only once during the initial model creation. Rather, it is intended as a tool to be continuously used for monitoring the model quality and as a trigger for further model adaptation iterations.

For the validation of models based on observations of the real system we suggest to use relative measures in the sense that a certain model X more appropriately represents the real system than a model Y.

The suggested validation approach itself can be characterized as operational results validation [Sargent 2005]. Due to the intended automated character of the validation, only statistical methods will be considered.

3. SUMMARY

This paper has introduced challenges in the area of automatic simulation model generation in the production and logistics context. It has analyzed and classified previous work and presented relevant challenges that exist in this context. Lastly this paper has presented work in progress that is currently being investigated by a PhD thesis.

References

Banks, J., Carson, J. S., Nelson, B. L., Nicol, D. M. (2004) Discrete-Event System Simulation (4th edition). Prentice Hall, 2004.

Boer, C., Saanen, Y. (2008) Controls: Emulation to Improve the Performance of Container Terminals. In: S. J. Mason, R. R. Hill, L. Mönch, O. Rose, T. Jefferson, J. W. Fowler (eds.): Proceedings of the 2008 Winter Simulation Conference, pp. 2639-2647.

Eckardt, F. (2002) Ein Beitrag zu Theorie und Praxis datengetriebener Modellgeneratoren zur Simulation von Produktionssystemen (A contribution to theory and praxis of data drive model generators for the simulation of production systems (in German)). Aachen, Shaker, 2002.

Fowler, J. W., Rose, O. (2004) Grand Challenges in Modeling and Simulation of Complex Manufacturing Systems. SIMULATION: The Society for Modeling and Simulation International, 80(9): 469–476, September 2004.

Gmilkowsky, P., Eckardt F., Palleduhn, D. (1998). Automated simulation model generation: a knowledge-based approach within an integrated system for modeling, simulation and analysis of discrete production processes. In: Proceedings of the Simulators International XV, ed. R. Ades, M.; Griebenow, 157–62: Society for Computer Simulation.

Hotz, I., Hanisch, A., Schulze, T. (2006) Simulation-Based Early Warning Systems as a Practical Approach for the Automotive Industry. In: L. F. Perrone, F. P. Wieland, J. Liu, B. G. Lawson, D. M. Nicol, and R. M. Fujimoto (eds.): Proceedings of the 2006 Winter Simulation Conference, pp. 1962-1970.

Jensen, S. (2007) Eine Methodik zur teilautomatisierten Generierung von Simulationsmodellen aus Produktionsdatensystemen am Beispiel einer Job Shop Fertigung (A method for semi-automatic generation of simulation models from production data systems for a job shop production system (in German)), Dissertation, Universität Kassel, 2007.

Kronberger, G., Kerschbaumer, B., Weidenhiller, A., Jodlbauer, H. (2006) Automated Simulation Model Generation for Scheduler-Benchmarking in Manufacturing. In: Proceedings of International Mediterranean Modeling Multiconference, Barcelona, 2006, pp. 45-50.

Lorenz, P., Schulze, T. (1995) Layout Based Model Generation. In: Alexopoulos, C., Kang, K. (eds.): Proceedings of the 1995 Winter Simulation Conference. ACM Press, pp. 728-735.

Randell, L., Bolmsjö, G. (2001) Database Driven Factory Simulation: A Proof-of-Concept Demonstrator. In: Peters, B. A., Smith, J. S., Medeiros, D. J., Rohrer, M. W. (eds.): Proceedings of the 2001 Winter Simulation Conference, pp. 977-983.

Rooks, T. (2009) Rechnergestützte Simulationsmodellgenerierung zur dynamischen Absicherung der Montagelogistikplanung bei der Fahrzeugneutypplanung im Rahmen der Digitalen Fabrik (Computer supported simulation model generation for dynamic validation of assembly logistics planning for new car models in the digital factory (in German)), Dissertation, TU Clausthal-Zellerfeld, 2009.

Reinhart, G., Selke, C. (2002) Information Becomes Knowledge – Automatic Building of Simulation Models. In: Proceedings of the 35th CIRP International Seminar on Manufacturing Systems, 13–15 May 2002, Seoul, Korea.

Sargent, R. (2005) Verification and Validation of Simulation Models. In: Kuhl, M. E.; Steiger, N. M.; Armstrong, F. B. and Joines, J. A. (eds.): Proceedings of the 2005 Winter Simulation Conference, pp. 121-130.

Selke, C. (2004) Entwicklung von Methoden zur automatischen Simulationsmodellgenerierung (Development of methods for automatic simulation model generation (in German). Dissertation, Technische Universität München, 2004.
Splanemann, R. (1995). Teilautomatische Generierung von Simulationsmodellen aus systemneutral definierten Unternehmensdaten (Semi-automatic generation of simulation models from system-neutral enterprise data (in German)). Bremer Schriften zur Betriebstechnik und Arbeitswissenschaft Band 5, Dissertation, Universität Bremen, 1995.
Wurdig, T. J., Wacker, R. (2008). Generische Simulationslösung für Fördertechnik (Generic Simulation for Conveyor Systems (in German). In: Raabe, M. (ed.) Advances in Simulation for Production and Logistics Applications, Fraunhofer IRB Verlag 2008, pp. 11-20.

Biography

Sören Bergmann is a PhD student at Ilmenau University of Technology. He is a member of the scientific staff at the Department for Industrial Information Systems. He received his diploma degree in Information Systems from Ilmenau University of Technology. Previously he worked as corporate consultant in various projects. His research interests include generation of simulation models and automated validation of simulation models within the digital factory context.

Steffen Strassburger is a professor at the Ilmenau University of Technology in the School of Economic Sciences. Previously he was working as head of the "Virtual Development" department at the Fraunhofer Institute in Magdeburg, Germany and as a researcher at the DaimlerChrysler Research Center in Ulm, Germany. He holds a Ph.D. and a Diploma degree in Computer Science from the University of Magdeburg, Germany. He is a member of the editorial board of the Journal of Simulation. His research interests include distributed simulation as well as general interoperability topics within the digital factory context. He is also the Vice Chair of SISO's COTS Simulation Package Interoperability Product Development Group. His web page can be found via www.tu-ilmenau.de/wi1.