World Academy of Science, Engineering and Technology
International Journal of Computer and Information Engineering
Vol:5, No:1, 2011

Sampling of Variables in Discrete-Event Simulation using the Example of Inventory Evolutions in Job-Shop-Systems Based on Deterministic and Non-Deterministic Data

Bernd Scholz-Reiter, Christian Toonen, Jan Topi Tervo And Dennis Lappe

Abstract**—**Time series analysis often requires data that represents the evolution of an observed variable in equidistant time steps. In order to collect this data sampling is applied. While continuous signals may be sampled, analyzed and reconstructed applying Shannon's sampling theorem, time-discrete signals have to be dealt with differently. In this article we consider the discrete-event simulation (DES) of job-shop-systems and study the effects of different sampling rates on data quality regarding completeness and accuracy of reconstructed inventory evolutions. At this we discuss deterministic as well as non-deterministic behavior of system variables. Error curves are deployed to illustrate and discuss the sampling rate's impact and to derive recommendations for its well-founded choice.

Keywords**—**discrete-event simulation, job-shop-system, sampling rate.

I. INTRODUCTION

DYNAMIC systems are often studied by simulations [1]-[3]. Here, the general approach is to run simulations and save the evolution of important variables throughout simulation by event-driven information or by sampling [2], [4]. Based on sampled data the temporal evolutions of variables can be reconstructed and analyzed. However, the quality of the reconstructed data depends highly on the accuracy of the samples. Here, we have a trade-off. Fixing the sampling rate beforehand to simulation at a very high frequency allows high quality reconstruction but may cause the collection of redundant data. That increases running time, memory requirements and the efforts of data analysis. On the other hand, too small sampling frequencies may impair data quality especially regarding accuracy. This trade-off is to be solved by the well-founded choice of the applied sampling rate [5].

The problem of reconstructing variable evolutions by sampled data is known from different sources and applications [5], [6]. As an example, analog data like experimental measurements or voices can be sampled, processed and reconstructed [7]. In that case errors within the reconstructed signals can be approximated by applying the Shannon-Nyquist sampling theorem [8]-[10]. Hereby, a sampling frequency of twice the highest frequency in the analog signal is needed to reconstruct accurately. However, the theorem is only applicable to band-limited analog signals. One possible solution to consider signals with a non-limited bandwidth is to apply a low-pass filter. Although data will be lost by this approach, the remaining signal becomes band-limited allowing for the sampling theorem to be applied. Thus, the signal can be reconstructed without errors. Today the application of Shannon's sampling theorem is common in many fields of science [6].

However, dealing with non-periodic and time-discrete signals the theorem is not suited for application. Therefore, simulation studies often document signal-relevant events and the time of their occurrences [1], [5]. This procedure allows collecting a minimum of necessary data. However, the investigation of dynamical properties of such systems requires time series analysis [11], [12]. Here, to apply advanced analysis methods like Fourier analysis and correlation analysis to the temporal evolution of important variables, data is required, that is taken in equidistant time increments [13]. Therefore, sampling is required to process the recorded event-driven information into data taken in equally measured time steps. Here, the sampling rate has to be chosen appropriately to ensure accurate data quality and the exclusion of information losses.

To investigate the impact of sampling frequency on data accuracy in discrete systems we consider inventory evolution in job-shop-systems. Here, the inventory evolutions are outcome of discrete objects, dependent processes and re-entrant structures resulting in often highly volatile developments [14], [15]. The inventory developments are discrete in time and value although between two changes of inventory the value remains constant forming a quasi time-continuous curve, fig. 1. In addition to being time-discrete and volatile, inventories in job-shop-systems are close to investigation, as detailed knowledge about the system's dynamics and the influence of certain system variables may

Bernd Scholz-Reiter is Full Professor at the University of Bremen, Germany, Managing Director of BIBA – Bremer Institut für Produktion und Logistik GmbH at the University of Bremen and Vice President of the German Research Foundation (DFG).

Christian Toonen, Jan Topi Tervo and Dennis Lappe are Research Scientists in the division Intelligent Production and Logistics Systems of BIBA - Bremer Institut für Produktion und Logistik GmbH at the University of Bremen, Germany. (corresponding author phone: +49-(0)421-218 5572; Fax No: +49-(0)421-218 5640; e-mail: too@biba.uni-bremen.de)

result in improved methods for the design and the production control of such systems [16].

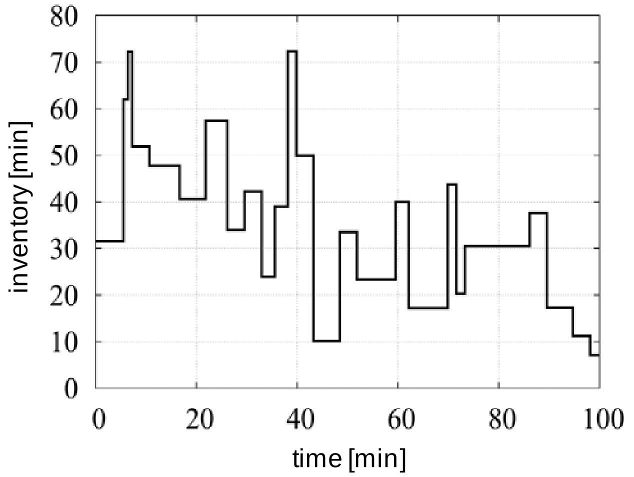

Fig. 1 Exemplified inventory evolution in job-shop-systems

In the following findings of a study using DES of job-shop-systems for the determination of an appropriate sampling rate for inventory evolutions are described. At this, deterministic as well as non-deterministic behavior of system variables is considered. In the next section we explicate about job-shop systems and introduce the applied DES-model. Then, we introduce the simulation study and present the results for deterministic and stochastic system variables.

II. Job-Shop-Systems And Model Description

Job-shop-systems are characterized by spatial and organizational units each of which incorporates machines or work stations of similar function. In this way so-called workshops are pooled up which contain concentrated knowledge and equipment. Their combined application in production is suited for heterogenic production programs with typically small and often changing quantities. Production orders move through this net of production units from workshop to workshop following their work plan. Thus, various production and transport processes success each other forming a discontinuous and strongly cross-linked material flow which can be characterized by complex and often non-linear inventory behavior [15], [17].

To design an appropriate simulation model initially a conceptual model was designed, fig. 2. This was followed by its implementation in an environment of discrete-event simulation within the software Tecnomatix Plant Simulation by Siemens, fig. 3. The model comprises various elements which can be combined in a generic way to represent any job-shop-system's configuration. Basic elements are workshops. One workshop comprises one or more similar capacity units. Each unit has one up-stream- and one down-stream buffer. The material flow is carried out by floor-borne transport vehicles connecting the modeled workshops, material entry and material exit. The number of workshops, machines and vehicles can be chosen arbitrarily, different transport distances can be considered by adequate transportation times.

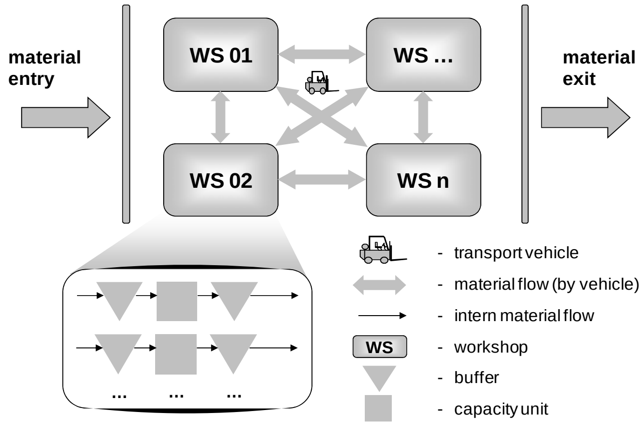

Fig. 2 Conceptual model for job-shop-systems [18]

Fig. 3 DES-Model of job-shop-systems

The order release starting the material flow within the system is controlled by the material entry. Here, the material input can be realized periodically or at random. The sequence of orders can be fixed within the related production program. Each order is linked to a work plan and a lot size, offering the possibility to generate orders of various processing steps and times. Once a production order is released, it makes its way through production following its work plan. The stopover time in each workshop is determined by the sum of waiting and processing times. At this, the sequence of processing at each capacity unit is given by the first come first serve principle. The allocation of incoming orders to capacity units is realized by considering lowest current inventory. Thus, in case a capacity unit is already processing an order, subsequent orders have to wait in the up-stream buffer. In case all transport vehicles are in operation another amount of waiting time may result after machining within the down-stream buffer. In this way various levels of inventory are queuing within up-stream and down-stream buffers quantified by their processing time. Once an order has been processed according to its work plan it exits the system through the material exit.

III. Sampling Of Inventory Evolutions

Previous studies showed that accurate sampling of inventory is not influenced by the dimensions of the production system but by the material entry time and by the durations of all operations within the system [19]. Therefore, within this study the applied model was restricted to a configuration comprising four workshops each containing three machines. The number of transport vehicles was chosen not being a bottleneck.

Initially, simulations with deterministic variables were studied. Different work plans were allocated containing minimum four up to sixty positions with various processing times. Order release was conducted periodically, simulated time exceeded 100.000 hours. The sampling was applied to the inventory evolution of one selected buffer applying varying sampling rates.

A. Ideal-, Over- and Undersampling

Within deterministic DES ideal-, over- and undersampling can be defined. Striving for no information losses each adopted inventory value throughout the simulation has to be captured. Therefore, the time increment between two sampled values must not exceed the smallest possible duration that an inventory value remains constant. Furthermore, to sample each change of inventory by the time of occurrence, all times within simulation and their sums must be generable by integer multiples of the sampling rate. In mathematical terms these requirements regarding the sampling rate correspond to the greatest common divisor (GCD) of all system times. Given that all times within the system (processing, transport, order release, …) are well-known beforehand to simulation the GCD of all durations t_{GCD} can be calculated by applying basic mathematics [20]. Then, optimal sampling frequency is given by

$$f_{opt} = f_{GCD} = (t_{GCD})^{-1} \tag{1}$$

Following the optimal sampling, which may be described as idealsampling, over- and undersampling can be defined referring to the applied sampling frequency f_s or the corresponding sampling distance ΔT_s [19]. After defining a frequency ratio Θ with

$$\Theta = \frac{f_s}{f_{GCD}} = \frac{t_{GCD}}{\Delta T_s} \tag{2}$$

we obtain

- undersampling: $\Theta < 1$,
- idealsampling: $\Theta = 1$ and
- oversampling: $\Theta > 1$.

Applying idealsampling we find that ΔT_s and t_{GCD} match each other. Therefore, the reconstructed inventory evolutions represent exactly the original curve. Thus, the reconstructed curve can be applied as reference graph. In contrast, undersampling as well as oversampling incorporates errors due to differences between the occurrence and the recording of an event. Exception is the oversampling with a frequency which is an integer multiple of the optimal frequency. Here, we receive accurate although redundant data.

B. Error Curves for Over- and Undersampling

Following over- and undersampling the errors occurring due to impaired data accuracy can be calculated applying the mean absolute error over time by

$$\overline{e}_{abs} = \frac{1}{T}\int_0^T \left| e_{abs}(t) \right| dt \tag{3}$$

Here, the absolute error $e_{abs}(t)$ is determined as the difference between reference graph and the reconstructed graph. Fig. 4 illustrates the small-scale diagram of the error curve $\overline{e}_{abs}$ which results by sampling a given inventory evolution by various sampling rates. The analyzed simulation run is based on $t_{GCD} = 40$ min.

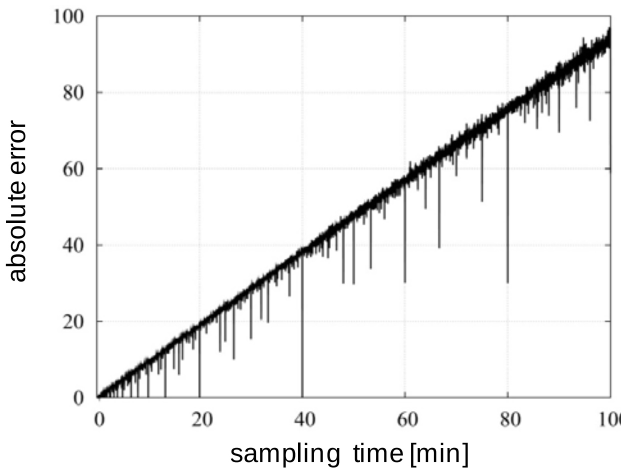

Fig. 4 $\overline{e}_{abs}$ in relation to sampling time (deterministic, small-scale)

Applying idealsampling meaning sampling distances of 40 min and a frequency ratio of $\Theta = 1$ the resulting error is $\overline{e}_{abs} = 0$. Equally, there results no error for oversampling with integer multiples of the idealsampling frequency. All other oversampling frequencies generate errors although these trend for increasing frequencies almost linearly to zero.

Equally, undersampling appears to develop with increasing sampling distances in nearly linear error evolution. However, plotted on large-scale for very large distances (very small frequencies) it becomes apparent, that the error develops in a declining way, fig. 5. Here, the error is limited by an upper bound which is determined by the system's parameters.

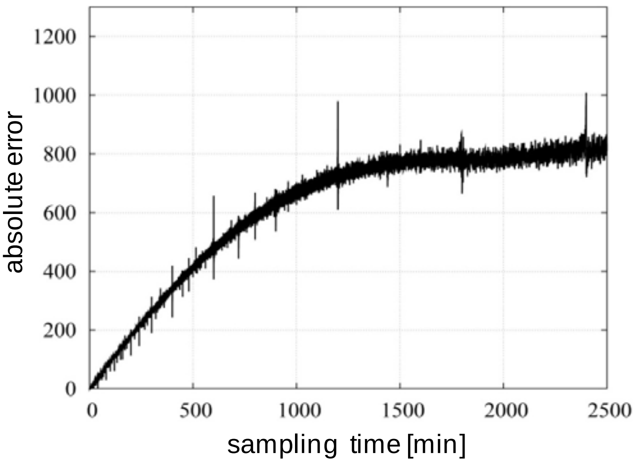

Fig. 5 $\overline{e}_{abs}$ in relation to sampling time (deterministic, large-scale)

An interesting effect within the deterministic scenario is the occurrence of outlier values within the error curves. The error is here either surprisingly low or high for certain sampling rates. The effect of low values appears in case the ratio of the greatest common divisor t_{GCD} and the applied sampling distance ΔT_s (and their corresponding frequencies accordingly) constitutes a positive rational number:

$$\Theta = \frac{t_{GCD}}{\Delta T_s} = \frac{n}{m}, \quad n, m \in \mathbb{N} \tag{4}$$

Assuming that the inventory value changes every time step given by t_{GCD}, m values are missed opposed to optimal sampling, however each n-th value is recorded exactly. Although this condition applies especially for small processing times with little variety it causes the occurrence and influences the intensity of these effects. Referring to fig. 4 by sampling each 80 minutes ($\Theta = \frac{1}{2}$) each second change of inventory is recorded correctly. Thus, temporarily there is no information loss. The same effect can be observed for oversampling, e.g. for a sampling time of 26,66 min. ($\Theta = \frac{3}{2}$). Here, every third value is documented within the moment of occurrence. Similar value interactions cause the outlier values with surprisingly high errors, fig. 5. Here, the sampling is executed frequently just before the inventory changes its value, thus boosting the overall error.

Although varying in details, the error curves for simulation runs with deterministic system variables and very long and highly volatile inventory evolutions resembled each other. However, the concrete appearance of an error curve is a result of sizes and variety of processing times, both influencing the volatility. This is particularly apparent regarding their outlier values. These dependences are elaborated in the next section for non-deterministic system variables.

C. *Impact of non-deterministic influences*

Following the simulation study on deterministic system variables another study was carried out to investigate the impact of non-deterministic influences on the previous results. Hereby, processing times within the work plans of the deterministic scenario were adjusted to incorporate normal distributions with varying widths of standard deviations. As a consequence, the GCD cannot be calculated beforehand to simulation anymore. Therefore, inventory changes have to be captured in time and in value throughout simulation to obtain data upon the inventory evolution.

Based on this data the GCD can be calculated after simulation. After determining all time-related differences between precedent and successive value changes the GCD can be computed in the same way as for the deterministic scenario. However, the stochastic influence has two main outcomes: Firstly, the variety of processing times increases, depending on the width of the defined standard deviation and the exactness of the saved data. Secondly, the GCD becomes smaller in the same amount as the exactness is enhanced. Generalizing this relationship we find that the GCD converges against zero the more precise the inventory values are documented. At the same time the volume of sampled data increases hyperbolically with $\frac{1}{t_{GCD}}$. Therefore, the exactness of the documented data has to be restricted. Although information is lost by this approach, it limits the data volume to suit individual constraints and requirements and allows for the GCD to be applied for sampling. In this study the exactness was restricted to an accuracy of one second.

Based on the recorded, event-driven data the inventory evolution was reconstructed. The resulting curve was used as a reference graph which allows determining the error curve for various sampling rates just as in the deterministic scenario.

Although appearing similar to the deterministic case the resulting error curves stand out because of diminished or absent outlier values, fig. 6. This is a consequence of the increased variety of processing times. While in the deterministic case there was less variety, the inventory changes and the sampling were much more probable to coincide. Within the non-deterministic scenario this effect loses its influence causing the error curve to narrow. Generalizing this effect we find that the reduction of processing times on the one hand and the stochastic-driven increase of variety on the other hand cause the error curve to trend gradually towards a smooth line.

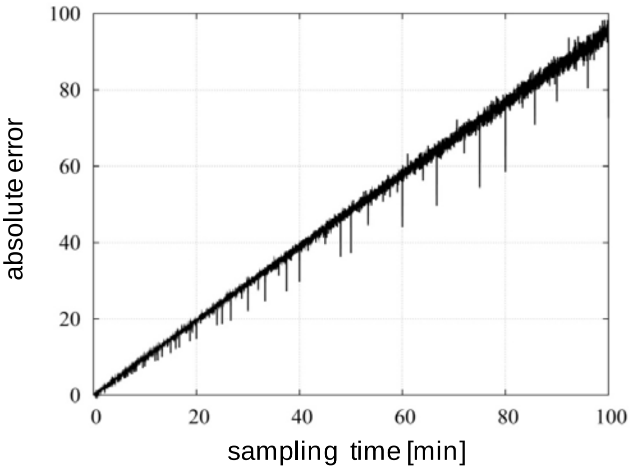

Fig. 6 $\overline{e}_{abs}$ in relation to sampling time (stochastic, small-scale)

IV. Conclusion

In this paper we introduced an approach which allows choosing a well-founded sampling rate to apply for the generation of equidistant data within time-discrete signals. Using the example of inventory evolutions in job-shop-systems it was demonstrated that data accuracy is ensured when applying a sampling frequency which corresponds with the greatest common divisor (GCD) of all system times. In case all times within the system are deterministic and well-known the GCD can be calculated beforehand to simulation. Applying lower or higher sampling rates generates errors discussed by error curves. Here, for increasing oversampling the error trends against zero while it converges against an upper bound for undersampling. In case the system times are not known or are subject to stochastic influences the events and times impacting the inventory value have to be documented. Then, the computation of the GCD is possible after simulation. Here, the simulation study showed that the error curve narrows for an increasing variety of processing times. Although applicable within the non-deterministic case, the GCD decreases by rising exactness of the documented variable values. This heightens data volume hyperbolically while the error declines only linearly.

Here, one way to deal with high data volume is to reduce the exactness of the documented data. Although details within the signal are lost by this approach, it allows for the GCD to be applied for the accurate sampling and reconstruction of the signal with acceptable data volumes. However, efforts and benefit of a high exactness have to be balanced individually in this case depending on accuracy requirements and capacity constraints. The reduction of exactness to allow applying the GCD can be seen as an analogy to Shannon's sampling theorem: although the bandwidth of a signal has to be limited, e.g. by employing a low-pass filter, it allows for the theorem to be applied.

Acknowledgment

This work was funded by German Research Foundation (DFG) under the reference number SCHO 540/15-1 "Application of Methods of Nonlinear Dynamics for the Structuring and Dimensioning of the Logistic System in Job-Shop-Systems".

References

[1] Banks, J. (ed.): Handbook of Simulation, Wiley and Sons, New York, 1998.
[2] Banks, J.; Carson, J.; Nelson, B.L.; Nicol, D.: Discrete-Event System Simulation, Prentice Hall, 2009.
[3] Zeigler, B.P.; Praehofer, H.; Kim, T.G.: Theory of Modeling and Simulation, Academic Press, 2000.
[4] Law, A.M.: Simulation Modeling and Analysis, McGraw-Hill Professional, 2007.
[5] Lohr, S.L.: Sampling: Design and Analysis, Duxbury Press, 1. edition 1999.
[6] Unser, M.: Sampling – 50 Years After Shannon. Proceedings of the IEEE, Vol. 80, No. 4, April 2000.
[7] Gold, B.: Speech and Audio Signal Processing, John Wiley & Sons, 1999.
[8] Shannon, C. E.: Communication in the Presence of Noise. In: Proceedings IRE. Vol. 37 (1949) 1, pp. 10-21.
[9] Marks II, R.J.: Introduction to Shannon Sampling and Interpolation Theory, Springer Verlag, New York, 1991.
[10] Stankovic, R.S.; Astola, J.T.; Karpovsky, M.G.: Some historic Remarks in Sampling Theorem, 2008.
[11] Li, H.; Muskulus, M.: Analysis and Modeling of Job Arrivals in a Production Grid. In: ACM SIGMETRICS Performance Evaluation Review, 34 (2007) 4, pp. 59-70.
[12] Radons, G.; Neugebauer, R.: Nonlinear Dynamics of Production Systems, Wiley-VCH Verlag GmbH & Co. KGaA, Weinheim, 2004.
[13] Kantz, H.; Schreiber, T.: Nonlinear Time Series Analysis. Cambridge University Press, Cambridge, 2004
[14] Scholz-Reiter, B.; Kleiner, M.; Nathansen, K.; Proske, G.: Chaos Control in Production Systems. In: Proceedings of the 15th IMACS World Congress on Scientific Computation, Modelling and Applied Mathematics, Vol. 5. Wissenschaft & Technik Verlag, Berlin, 1997, pp. 701-706.
[15] Scholz-Reiter, B.; Freitag, M.; Schmieder, A.: A dynamical approach for modelling and control of production systems. In: Boccaletti, S. et al. (ed.) Proc. 6th Experimental Chaos Conference, AIP Conference Proceedings 622 (1), 2002, pp. 199-210.
[16] Scholz-Reiter, B.; Toonen, C.; Tervo, J.T.: Investigation of the Influence of Capacities and Layout on a Job-Shop-System's Dynamics. Proceedings of the 2nd LDIC - International Conference on Dynamics in Logistics 2009. In Print.
[17] Katzorke, I.; Pikovski, A.: Chaos and Complexity in a Simple Model of Production Dynamics. In: Discrete Dynamics in Nature and Society, Vol. 5 2000, pp. 179-187.
[18] Scholz-Reiter, B.; Toonen, C.; Tervo, J.T.; Lappe, D.: Einfluss der Abtastrate auf Ergebnisse der ereignisdiskreten Simulation. In: ZWF - Zeitschrift für wirtschaftlichen Fabrikbetrieb 105 (2010) 3, pp. 211-215.
[19] Scholz-Reiter, B.; Toonen, C.; Tervo, J.T.; Lappe, D.: Einfluss der Abtastrate auf die Fehlerentstehung in der Auswertung ereignisdiskret simulierter Werkstattfertigungen. In: Industrie Management 26 (2010) 6. In Print.
[20] Bronstein, I.N.; Semendyayev, K.A.; Musiol, G., Muehlig, H.: Handbook of Mathematics. Springer Verlag, Berlin, 5. ed. 2007.

Prof. Dr.-Ing. **Bernd Scholz-Reiter** (born in 1957) holds a degree in Industrial Engineering from the Technical University Berlin (TUB). Following his PhD (TUB, 1990), Bernd Scholz-Reiter served as post-doctoral fellow in the department for Manufacturing Research at IBM T.J. Watson Research Center in Yorktown Heights, U.S.A. In 1991 he returned to Germany to become Assistant Professor in the Faculty of Computer Science at Technical University Berlin.

From 1994 to 2000 he held the Chair for Industrial Information Systems at the newly founded Brandenburg Technical University at Cottbus, Germany. In 1998 he founded the Fraunhofer Application Center for Logistic Systems Planning and Information Systems in Cottbus, which he headed until 2000.
Since November 2000 Bernd Scholz-Reiter is full professor and holds the new Chair for Planning and Control of Production Systems at the University of Bremen, Germany. Since 2002 he also serves as Managing Director of the BIBA - Bremer Institut für Produktion and Logistik GmbH at the University of Bremen.
His research expertise is in the fields of logistics, distributed production systems, process modelling and simulation as well as the planning and control of production systems with a special focus on autonomous control. In 2005 Bernd Scholz-Reiter initiated the Bremen Log Dynamics Research Cluster with its integrated International Graduate School for Dynamics in Logistics. He is spokesperson of several large research projects (funded by e.g. Deutsche Forschungsgemeinschaft DFG, Federal Ministry of Economics and Technology, Volkswagen Foundation, European Commission). He is a member of several international academies of science (e.g. German Academy of Science and Engineering – acatech, Berlin-Brandenburg Academy of Sciences and Humanities, International Academy for Production Engineering – CIRP). Since July 2007, Bernd Scholz-Reiter is Vice President of the German Research Foundation (DFG).

Dipl.-Wirt.-Ing. **Christian Toonen** (born in 1979) holds a degree in Industrial Engineering and Management from the University of Siegen. Since October 2006, Christian Toonen works as a Research Scientist in the division Intelligent Production and Logistics Systems of BIBA - Bremer Institut für Produktion und Logistik GmbH at the University of Bremen, Germany.

Dipl.-Phys. **Jan Topi Tervo** (born in 1978) holds a degree in Physics from the University of Göttingen. Since March 2005 Jan Topi Tervo works as a Research Scientist in the division Intelligent Production and Logistics Systems of BIBA - Bremer Institut für Produktion und Logistik GmbH at the University of Bremen, Germany.

M.Sc. **Dennis Lappe** (born in 1985) holds a degree in Systems Engineering from the University of Bremen. Since January 2010 Dennis Lappe works as a Research Scientist in the division Intelligent Production and Logistics Systems of BIBA - Bremer Institut für Produktion und Logistik GmbH at the University of Bremen, Germany.