Proceedings of the 2019 Winter Simulation Conference
N. Mustafee, K.-H.G. Bae, S. Lazarova-Molnar, M. Rabe, C. Szabo, P. Haas, and Y.-J. Son, eds.

SIMULATION-BASED OPTIMIZATION OF SEQUENCING BUFFER ALLOCATION IN AUTOMATED STORAGE AND RETRIEVAL SYSTEMS FOR AUTOMOBILE PRODUCTION

Christian Urnauer
Eva Bosch
Joachim Metternich

Institute of Production Management, Technology and Machine Tools
Technische Universität Darmstadt
Otto-Berndt-Straße 2
Darmstadt, 64287, GERMANY

ABSTRACT

In production control with a stable order sequence, the assembly order is fixed in the form of the so-called pearl chain. However, parallelism and instabilities in the production process cause scrambling in the order sequence. The stability of the order sequence can be increased by using sequencing buffers between the individual production units. In the automobile industry, all sequencing buffers frequently share one large automated storage and retrieval system (AS/RS) with limited capacity. In existing approaches for dimensioning sequencing buffers, this shared capacity restriction is not considered, even though the optimal distribution of buffer capacity might be an important lever for increasing the sequence stability. Therefore, the focus of this paper is the identification of the optimal capacity distribution between several sequencing buffers using the same storage area. A greedy simulation-based improvement heuristic is developed which makes it possible to find promising solutions with a practical and intuitive optimization approach.

1 INTRODUCTION

Particularly in the German automobile industry the “pearl chain” (German: “Perlenkette”) is a popular production control concept. It implies that production orders are strung like pearls in a chain (Weyer and Spath 2001). The advantages of this concept are better planning due to a fixed sequence preview called the “frozen zone” and reduced complexity due to a hybrid control with push and pull elements (Klug 2010). To assure that this planned order sequence can be maintained all through the production process, it is necessary to have buffers in which the sequence can be reshuffled. Their purpose is to reorder the car bodies in a way that they can be introduced into the subsequent production unit in the planned sequence. Especially frequent process failures in the body and paint shops make buffers necessary (Meyr 2004) since scrambled assembly sequences result in substantial waste in the whole supply chain (Gusikhin et al. 2008). As a consequence, order lead times become unstable and on-time delivery to the customer can be endangered. Therefore, the buffers are positioned between the body and paint shop or between the paint shop and assembly. Figure 1 shows this common layout of body shop, paint shop and assembly, each unit separated by a sequencing buffer. In practice, however, it is common to use one centralized AS/RS with limited capacity as a buffer (Figure 2) in which storage positions are allocated to the individual resequencing points of the production process (Klug 2010). For instance, in a Volkswagen plant in Germany an AS/RS with a capacity of 1,000 buffer positions reshuffles the order sequences between three production units (Boysen et al. 2012). In the next section the two most relevant performance measures for sequence stability are introduced and the problem formulation is presented. Section 3 presents the structure of the simulation model, which is used to analyze the problem and to build a simulation-based heuristic for it. The description of the developed heuristic along with its evaluation follows in Section 4. Section 5 concludes the paper.

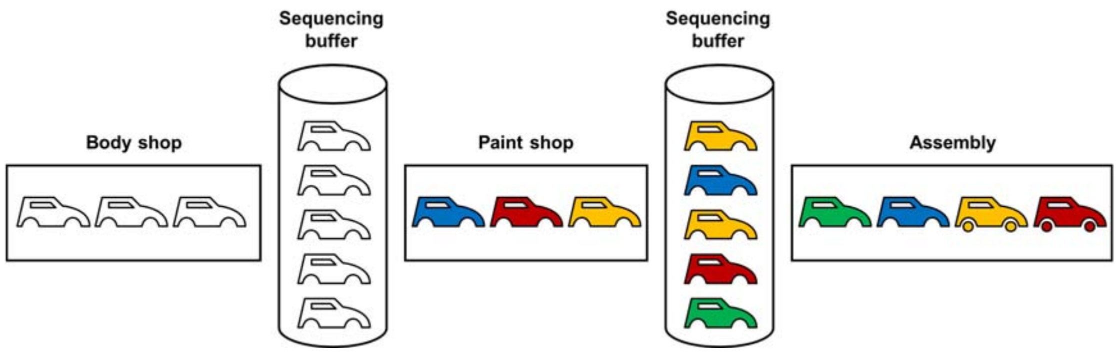

Figure 1: Sequencing buffers and workshops in automobile production.

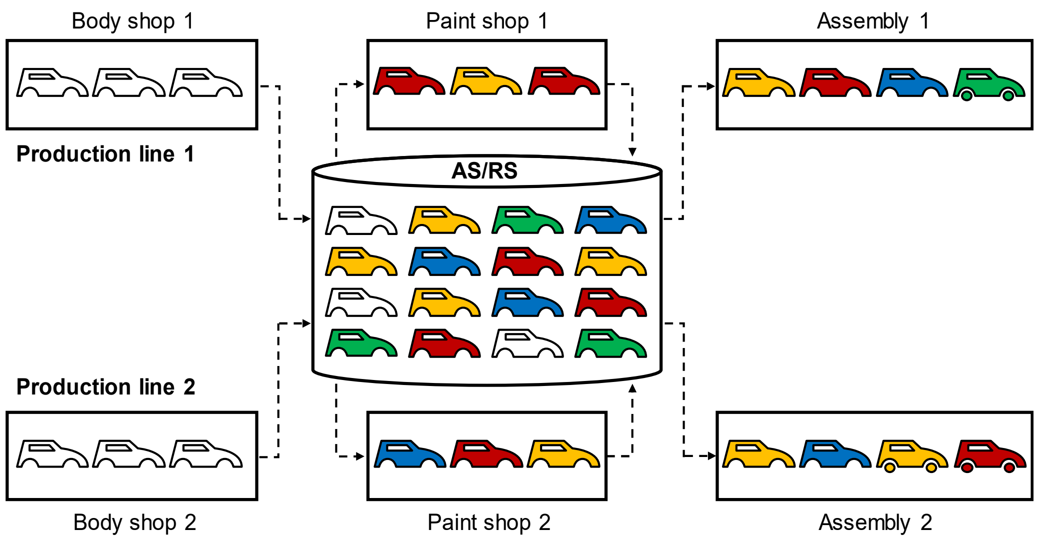

Figure 2: Resequencing in central AS/RS.

2 PROBLEM DESCRIPTION

In existing approaches for dimensioning sequencing buffers, the joint capacity restriction is not taken into account (Boysen et al. 2012). Also in the literature on AS/RS, there is no approach that deals with the allocation of buffer positions for the purpose of resequencing (Roodbergen and Vis 2009). Meißner (2010) and Weyer (2002) propose simple dimensioning rules for single sequencing buffers based on maximum occurring deviations or low runner frequencies. Inman (2003) presents two algorithms to realize a desired sequence quality with an accordingly sized buffer based on given scrambling data. Ding and Sun (2004) consider the specific situation that car bodies are stored in the AS/RS while defect parts are repaired, including the option to pre-produce spare cars to bridge that time. According to VDA (2016), buffer design and sequence stability are subjects of plant simulation. However, a concrete approach for buffer dimensioning is not given. This paper analyzes the sequencing buffer allocation problem using Monte Carlo simulation and proposes a simulation-based heuristic to solve it.

The objective is to increase sequence stability in the whole production process, which is assessed with the two main performance measures: *sequence adherence (SA)* and *average absolute sequence deviation (ASD)* (Meißner 2010). SA is a quantitative measure that provides information on how many sequence violations v_k occur in a sequence in relation to its length n (1). Here, only delays are counted as violation (2).

$$SA = 1 - \frac{1}{k}\sum_{k=1}^{n} v_k [\%] \tag{1}$$

$$with\ v_k = \begin{cases} 1 & if\ actual\ position > target\ position \\ 0 & otherwise \end{cases} \tag{2}$$

The actual extent of the scrambling is described by ASD which is calculated as shown in (3) and (4). For each element in the sequence, the extent of its deviation from its target position is calculated. The sum of their absolute values divided by the length of the considered sequence gives the ASD.

$$ASD = \frac{1}{n}\sum_{k=1}^{n}|SD_k| \tag{3}$$

$$with\ SD_k = actual\ position - target\ position \tag{4}$$

Given a restricted number of buffer positions c, the problem is to maximize the sequence stability SA by finding the best allocation among a given number m of sequencing buffer locations x_i. The vector X represents the decision variables in the objective function $SA(X)$ (5). The capacity restriction is modeled by Equation (6).

$$max\ SA(X)\ with\ X = \begin{pmatrix} x_1 \\ \vdots \\ x_m \end{pmatrix} \tag{5}$$

$$\sum_{i=1}^{m} x_i \le c \tag{6}$$

Maximizing SA is chosen as the objective since the number of violations is the major cause for waste. Improving sequence stability by increasing sequencing buffer sizes, however, depends highly on the extent of the occurring deviations (Inman 2003). For this reason ASD is measured to create test instances in the developed simulation model.

3 SIMULATION MODEL

Since the sequencing buffer allocation problem is part of a dynamic production environment with too much complexity to be solved analytically, a simulation model is used to imitate the operation of the real-world system over time (Banks 1998). Hence, the dynamics of a problem can be mapped into the model. Simulation is particularly useful for problems in production environments since in a real world production, there are a variety of boundary conditions like the order spectrum, the personnel, machine, or tool capacity, that change frequently and can therefore not – or only limitedly – be compared in experiments with different variable specifications (Alrabghi and Tiwari 2015). For this reason, simulation is used for various problems in the automobile industry (Williams and Ülgen 2012). In the case at hand, a Monte Carlo simulation model with an appropriate aggregation level was developed to make an efficient application of optimization approaches possible. The proposed algorithm can, however, also be used with other simulation methods, such as discrete event simulation, which is commonly used in the automobile industry.

The central components of the model are the production units (body and paint shops) and the sequencing buffers. The former create scrambling in the car sequence and the latter reshuffle it so that the original sequence can be recovered by the subsequent production unit to the greatest extent possible. In the following paragraphs, the order sequence generation, the scrambling of the sequence and the function of the sequencing buffer in the implemented simulation model are outlined (Figure 3).

3.1 Order Sequence Generation

Especially in car production, sequencing methods are applied to minimize work overload and level part usage (Boysen et al. 2009). In the simulation presented in this paper, the car sequencing applied seeks to achieve equally distributed body types among the order sequence. Besides the number of body types b, the number of colors c, and the relative frequency of the rarest low runner f_{LR} can be varied in the simulation model. These attributes are relevant for the resequencing capability because they implicitly define the probability that two identical models are in the buffer at the same time (see Section 3.3). Figure 4 exemplarily illustrates such a sequence with 5 body types, 5 different colors and a low runner frequency of 6 %. The horizontal axis represents the positions of the orders in a sequence of 100 cars length. The vertical axis separates the orders by their underlying body type. The color of each car is indicated by the color of the dots applied in the diagram.

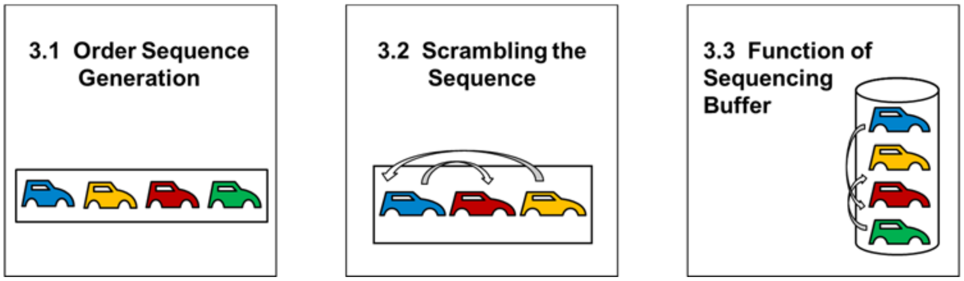

Figure 3: Elements of the simulation model.

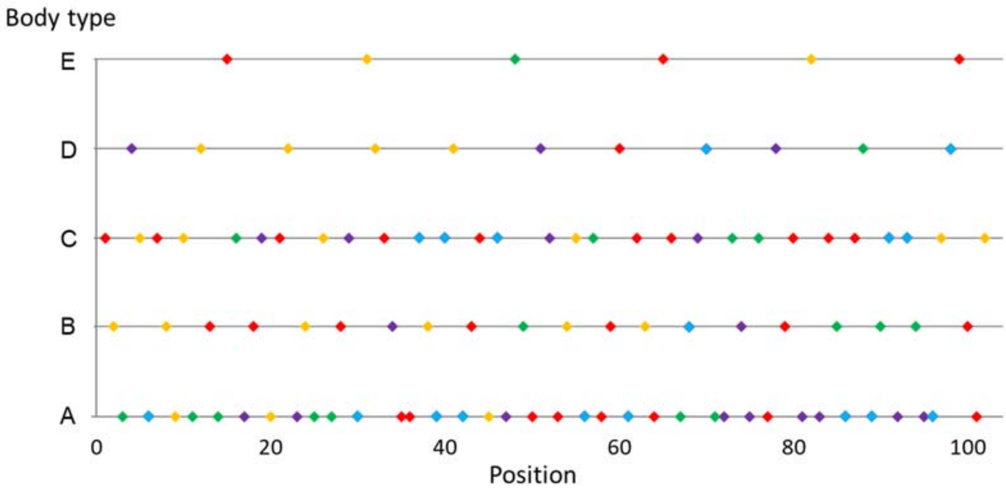

Figure 4: Example for the simulated model mix.

3.2 Scrambling the Sequence

The scrambling that emerges from the production units is modelled in accordance with Gusikhin et al. (2008). They create new output positions for a given input sequence by adding an exponentially distributed random number to each element in the input sequence. The scrambled output sequence is then generated by sorting the new output position numbers in ascending order and subsequently assigning the new output positions. If some elements have the same output position number, they are ordered in accordance with their position number in the input sequence. To generate data with a realistic distribution structure in a broader range, a gamma distribution $\gamma(\alpha, \beta)$ is used, which is a direct generalization of the exponential distribution. While an exponential distribution can only be adjusted via its scale parameter λ, a gamma distribution allows for more accurate modeling of the sequence scrambling via the shape parameter α and the scale parameter β. Figure 5 shows how the resulting *ASD* depends linearly on the parameters α and β, allowing any desired extent of scrambling to be modelled.

3.3 Function of Sequencing Buffer

Besides physically reordering the sequence, the concept of virtual resequencing has been proven to be promising (Inman and Schmeling 2003) and is already state of the art in the automobile industry. In an agile assembly-to-order system, car bodies are not strictly bound to an order number throughout the production process. With virtual resequencing it is not necessary to search the exact order in a buffer but only a car body that has the same characteristics, i.e. the same body type (and color). In the simulation model, resequencing is implemented as described in the following. In each takt one car body exits the buffer towards the subsequent production unit and another car body arrives in the buffer after completing the preceding production step. The term "takt" describes the time span between the production start points of two successive cars. The implemented resequencing logic determines which order is taken out of the buffer in the next step.

Figure 6 illustrates this process in a flow chart – assuming that the indices of the takt are equal to the numbering of the order positions in the target sequence. The process starts in takt $t = 1$ searching for the first order a that is supposed to be taken from the buffer. If the ordered car body is physically stored in the buffer or another car body can be provided by performing a virtual swap, the next order is determined and the algorithm proceeds to the next takt. In case it is not possible to find a matching car body in the buffer, the next best order is attempted to be served. In this way, the lowest possible sequence deviations can be assured. The number of the pending order with the earliest planned time is then not equal with the takt anymore but corresponds to the order with the greatest delay. The algorithm terminates by reaching the last takt T in the simulation.

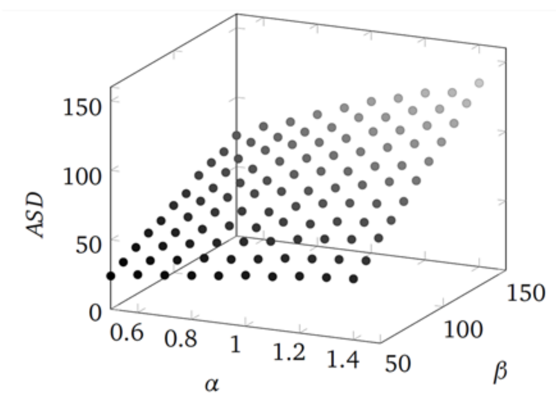

Figure 5: ASD resulting from different parameter settings in gamma distribution.

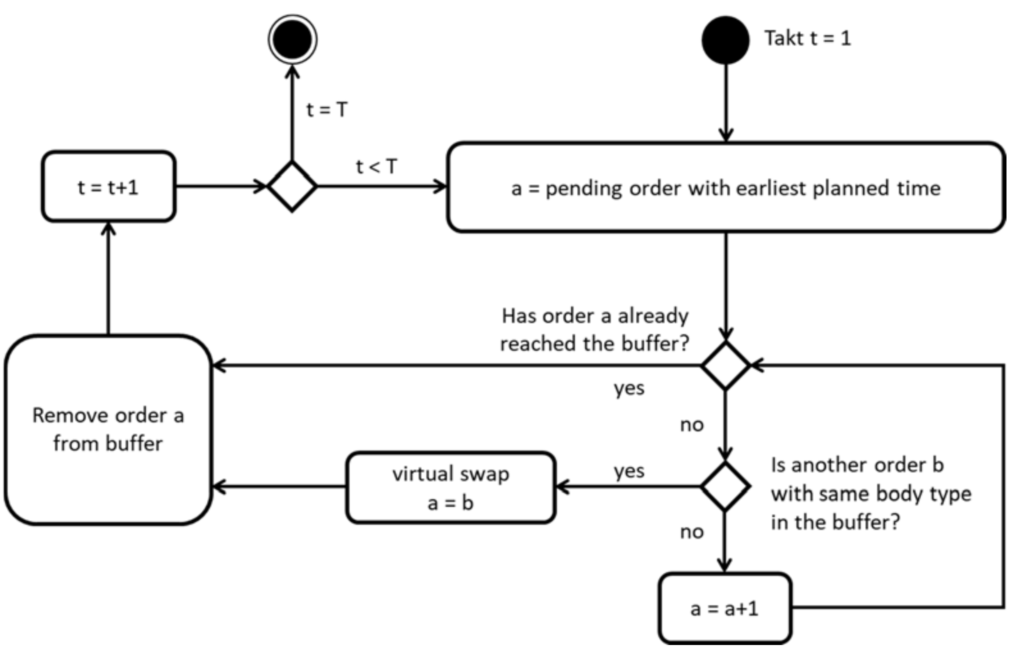

Figure 6: Flow chart of resequencing process.

The most relevant performance measure for the resequencing capability of a sequencing buffer is ASD since the extent of deviation is critical for the ability to restore a given sequence (Inman 2003). The sequencing buffer is characterized by the attribute capacity x_i, which describes the number of storage positions that are available for buffering at the location i. Figure 7 shows how the resequencing capability of a buffer increases with increasing capacity. It is characteristic, that the achievable sequence adherence grows rapidly with increasing number of buffer positions when buffers are small and transitions into a saturation range in which additional buffer positions have decreasing impact on the resulting sequence quality. To reach $SA = 100\ \%$, buffers would have to be large enough to catch up the greatest delay.

The number of buffer positions required to ensure a given value of SA increases with higher ASD. For example, approximately 200 buffer positions are necessary to ensure a SA of 90% for a sequence with an ASD of 109.6 (red line) whereas only 80 are required when the ASD equals 39.2 (light blue line).

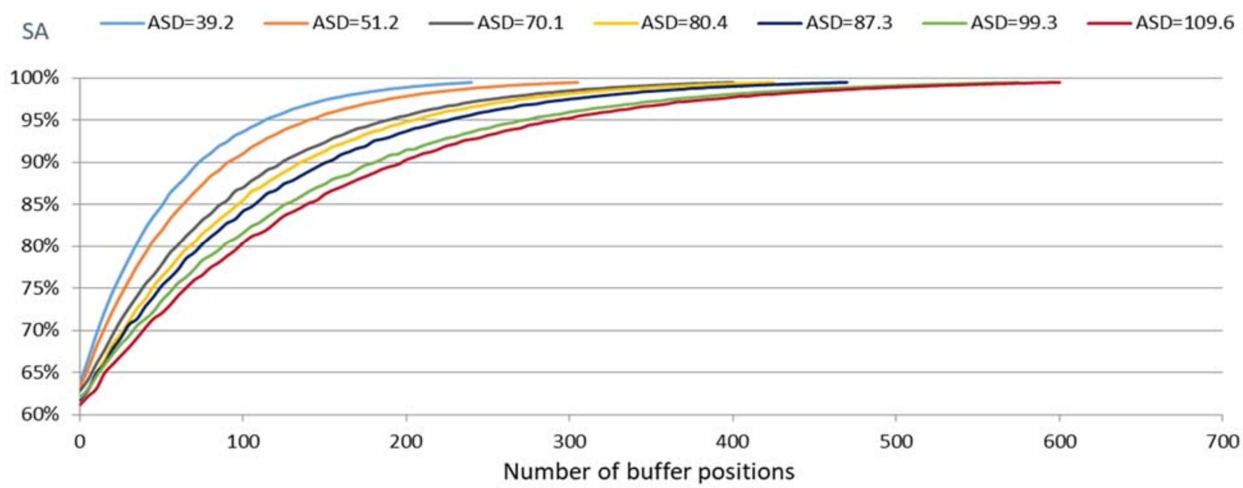

Figure 7: Resequencing capability depending on the number of buffer positions.

3.4 Implementation

The simulation is implemented in Java 1.8. The two introduced sequence performance metrics are used as evaluation criteria. To avoid horizon effects, the key figures are calculated from the mid 8,000 positions in an order sequence of 10,000 cars. Each simulation experiment consists of as many runs as needed to ensure on a confidence level of 95 %, that the observed performance measures are within an interval of +/- 0.5 % around their average.

4 OPTIMIZATION OF SEQUENCING BUFFER ALLOCATION

While simulation is used to test an existing solution, an optimization procedure can be used to generate and improve a solution to a given problem (Eley 2012). In the following, an optimization method based on the previously introduced Monte Carlo simulation is presented.

According to VDI (2013) simulation and optimization are either linked sequentially or hierarchically. With sequential linking, either simulation is performed first, followed by optimization, or vice versa. In both cases, the results of the first phase serve as input for the second phase. In this work, the optimization acts as the leading component and is hierarchically linked with the simulation, which is used to calculate the target value. The optimization iteratively generates new values for the variables and evaluates them by using the simulation.

Pre-studies on the presented simulation model indicate that the solution space is convex. With this information on hand, a greedy hill climbing heuristic is a promising approach to find optimal solutions in short time. Figure 8 illustrates the procedure of the optimization algorithm. The initial solution X contains a valid allocation of the AS/RS capacity among the m resequencing locations (line 1). It is stored as the first best solution (line 2). From there on, the marginal utility $\Delta SA/\Delta x_i$ for additional buffer space is analyzed for every x_i (line 4) with x_i being the capacity of resequencing buffer i. For the approximation, an (invalid) scenario is simulated in which the regarded variable is assigned 10 more buffer positions while the values of all other variables remain the same. The experiments needed for these approximations are independent and can therefore be parallelized. Pre-studies have shown that changes in x yield to only small changes in SA. For this reason, an increase of 10 positions is chosen for the gradient calculation.

1 **Function** *Optimization (start solution X)*
2   best solution $X_{best} = X$;
3   **repeat**
4   gradient approximation $\frac{\Delta SA}{\Delta x_i}$ using simulations with $x_i = x_i + 10$ $\forall x_i \in X$;
5   Choose new allocation X greedy: move y buffer positions from x_i with lowest $\frac{\Delta SA}{\Delta x_i}$ to x_j with highest $\frac{\Delta SA}{\Delta x_j}$;
6   calculate $SA(X)$ using simulaion;
7   **if** $SA(X) > SA(X_{best})$ **then**
8       $X_{best} = X$;
9   **end**
10   **until** *stop criteria reached*;
11   Output X_{best};

Figure 8: Procedure of the simulation based optimization.

In the next step, the variable with the lowest gradient is reduced by y positions and the variable with the highest gradient is increased by the same amount of capacity (line 5) because the highest increase in the objective value is expected by performing this swap. The number of buffer positions y to be switched between the resequencing locations is previously defined (in this example it is always fixed). The new objective function value SA of the resulting candidate solution is calculated using simulation (line 6). If it exceeds the best known objective function value, the incumbent best solution X_{best} is replaced by the current one (lines 7-9). The stop criterion in line 10 is reached, when no improvement has taken place over a period of z iterations. This hedge is necessary, since both the approximation and the calculation of the objective function value are using average values from stochastic experiments. Pre-studies were carried out on two simulation scenarios to iteratively fine tune the parameters y and z as well as the width of the confidence interval. A good tradeoff between calculation time and objective function value could be reached with $y = 3$, $z = 7$, and an interval width of 3.5 %. The objective function value was hardly influenced by any of the varied parameters and the calculation time was mainly influenced by the confidence interval in which the average SA is demanded to lie within.

An exemplary search process of the optimization algorithm is illustrated in Figure 9, showing a case in which there are two production lines with two sequencing buffers in each line (as it can be seen in Figure 2). Buffers 1 and 2 are in the first production line, buffers 3 and 4 in the second one. Buffers 1 and 3 are positioned after the body shops and numbers 2 and 4 are placed after the paint shops. The overall AS/RS capacity is 904. The body and paint shops are chosen with different intensities in the scrambling that they cause. The body shop in line 1 is using the parameters $\alpha = 1.1, \beta = 90$ (ASD $= 70.1$), the one in line 2 is using $\alpha = 1.0, \beta = 70$ (ASD $= 51.2$). The paint shops are using $\alpha = 1.3, \beta = 100$ (ASD $= 87.3$) in line 1 and $\alpha = 1.2, \beta = 125$ (ASD $= 99.3$) in line 2. The ASD values in brackets are the expected average sequence deviations if the input sequence was undisturbed. The four settings correspond with the cases 3, 2, 5, and 6 in Figure 7. All buffers start with the same number of allocated positions (226) in the AS/RS. Figure 9 shows how SA is increasing during the search until it reaches a saturation. In the first iterations, there are many exchanges between the variables, and in the course of time they become less and less frequent until a range is reached in which no swaps take place anymore (starting at iteration 56) which terminates the algorithm. The result is an allocation of 222/240/181/261 positions to buffers 1 to 4 which leads to the objective function value SA = 95.93 %. The improvement of 0.21 % may seem small, but given that non-compliance of the assembly sequence leads to significant waste along the whole value chain, even small improvements have valuable impact on the production performance.

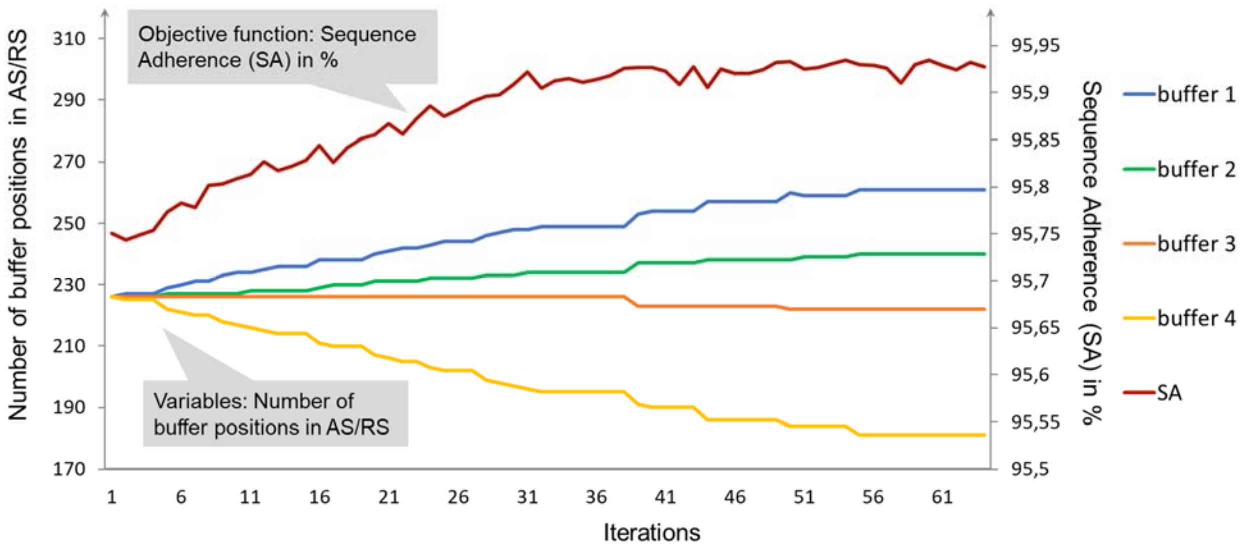

Figure 9: Exemplary search procedure.

The optimization approach was tested in a simulation study with a broad range of different scenarios in which the parameter specifications were varied in the following way:

- Layouts with one to four production lines
- Production lines with both, one (only after the paint shop) or two sequencing buffers
- Variation of the number of body types, number of colors, and low runner frequency in three steps
- Seven different scrambling intensities in the simulated production units

Overall, 22 scenarios were tested in which each of the stated characteristics was analyzed both in an isolated manner and in a complex environment. To explore the solution space and to evaluate the quality of the algorithm's solutions, a wide net of measuring points was defined and tested for each scenario. Depending on the tested case, up to 8,748 different measuring points were simulated. Each of these points represents another constellation of variable assignments. The analysis confirmed the assumption that the solution space is convex and led to the result that the solution found by the optimization approach has the best objective function value in every tested scenario. This leads to the conclusion that the found solutions are approximately globally optimal. The computation time of the optimization approach mainly depends on the problem size, i.e. the number of considered production lines and production units. The average computation time for the scenarios with one production line was 93 sec, for two lines 630 sec, for three lines 2,253 sec, and for four production lines it was 2,707 sec.

5 CONCLUSION

Sequencing buffers are used to improve the stability of the order sequence in an environment of instabilities and parallelism in production processes. In automobile industry, frequently one shared AS/RS is providing buffer space for all resequencing points in different production lines. So far, there exists no approach for the optimal allocation of these buffer capacities. Therefore, the focus of this paper is the identification of the optimal capacity distribution between several resequencing points using the same storage area.

For this, a simulation-based improvement heuristic is developed. Since preliminary studies on the developed simulation model indicated that the solution space is convex, a greedy hill climbing heuristic is a promising approach to find optimal solutions in short time. Starting with a valid solution, the marginal utility for additional buffer space is analyzed for every sequencing point. The performance measures SA and ASD are used to evaluate the different solutions. The evaluation on a large, diversified test set shows that the heuristic reliably finds promising solutions with the suspicion to be approximately globally optimal.

In further studies, a dynamically varying buffer capacity allocation could be taken into account. Another aspect to be considered is paint batching, which combines orders of the same color into one lot to reduce changeover costs resulting from color changes and cleaning. The buffer space for this purpose could be taken from the same AS/RS that provides the storage space for resequencing buffers which makes it a combined optimization problem. This work serves as the basis for future research projects on buffer space allocation problems under consideration of sequence stabilities.

REFERENCES

Alrabghi, A. and A. Tiwari 2015. "State of the Art in Simulation-based Optimisation for Maintenance Systems". *Computers & Industrial Engineering* 82:167–182.

Banks, J. 1998. "Principles of Simulations". In *Handbook of Simulation. Principles, Methodology, Advances, Applications, and Practice*, edited by J. Banks, 3–30. New York: John Wiley & Sons.

Boysen, N., M. Fliedner, and A. Scholl 2009. "Sequencing Mixed-Model Assembly Lines: Survey, Classification and Model Critique". *European Journal of Operational Research* 192(2):349–373.

Boysen, N., A. Scholl, and N. Wopperer 2012. "Resequencing of Mixed-Model Assembly Lines: Survey and Research Agenda". *European Journal of Operational Research* 216(3):594–604.

Ding, F.-Y. and H. Sun 2004. "Sequence Alteration and Restoration Related to Sequenced Parts Delivery on an Automobile Mixed-Model Assembly Line with Multiple Departments". *International Journal of Production Research* 42(8):1525–1543.

Eley, M. 2012. *Simulation in der Logistik. Eine Einführung in die Erstellung ereignisdiskreter Modelle unter Verwendung des Werkzeuges "Plant Simulation".* Berlin: Springer.

Gusikhin, O., R. Caprihan, and K. E. Steck 2008. "Least In-Sequence Probability Heuristic for Mixed-Volume Production Lines". *International Journal of Production Research* 46(3):647–673.

Inman, R. R. 2003. "ASRS Sizing for Recreating Automotive Assembly Sequences". *International Journal of Production Research* 41(5):847–863.

Inman, R. R. and D. M. Schmeling 2003. "Algorithm for Agile Assembling-to-Order in the Automotive Industry". *International Journal of Production Research* 41(16):3831–3848.

Klug, F. 2010. *Logistikmanagement in der Automobilindustrie. Grundlagen der Logistik im Automobilbau.* Berlin: Springer.

Meißner, S. 2010. "Controlling Just in Sequence Flow-Production". *Logistics Research* 2(1):45–53.

Meyr, H. 2004. "Supply Chain Planning in the German Automotive Industry". *OR Spectrum* 26(4): 447–470.

Roodbergen, K. J. and I. F.A. Vis. 2009. "A Survey of Literature on Automated Storage and Retrieval Systems". *European Journal of Operational Research* 194(2):343–362.

VDA. 2016. "Implementation Instruction Process Simulation in the Automotive and Automotive Component Supply Industry". http://www.vda-ablaufsimulation.de/images/5/53/Implementation_instruction_VDA_Vers2-6_20160418.pdf, accessed 26th August.

VDI. 2013. "Simulation of Systems in Materials Handling, Logistics and Production". VDI Richtlinie 3633. Berlin: Beuth Verlag GmbH.

Weyer, M. and D. Spath 2001. "Das Produktionssteuerungskonzept "Perlenkette"". *Zeitschrift für wirtschaftlichen Fabrikbetrieb* 96(1-2):17–19.

Weyer, M. 2002. *Das Produktionssteuerungskonzept Perlenkette und dessen Kennzahlensystem*. Karlsruhe: Helmesverlag.

Williams, E. J. and O. M. Ülgen 2012. "Simulation Applications in the Automotive Industry". In: *Use Cases of Discrete Event Simulation. Appliance and Research*, edited by S. Bangsow, 45–58. Berlin: Springer.

AUTHOR BIOGRAPHIES

CHRISTIAN URNAUER is a Research Assistant at the Institute of Production Management, Technology and Machine Tools (PTW) at Technische Universität Darmstadt. He is part of the *Center for industrial Productivity* (CiP) and his research interests are in holistic planning of production systems and in-house material flows using process mining, simulation, and mathematical optimization. He holds a Master of Science in Industrial Engineering which he obtained at Technische Universität Darmstadt. His e-mail address is c.urnauer@ptw.tu-darmstadt.de.

EVA BOSCH is a Research Assistant and Chief Engineer at the Institute of Production Management, Technology and Machine

Tools (PTW) at Technische Universität Darmstadt. Her research interests include cutting tool management in general and especially smart tools and the simulation of the tool cycle. She holds a Master of Science in Industrial Engineering which she obtained at RWTH Aachen after finishing her Bachelor of Science at Technische Universität Kaiserslautern. Her e-mail address is e.bosch@ptw.tu-darmstadt.de.

JOACHIM METTERNICH is a Professor and Director at the Institute of Production Management, Technology and Machine Tools (PTW) at Technische Universität Darmstadt. After obtaining his PhD he gained industry experience at TRUMPF Werkzeugmaschinen GmbH & Co. KG, BOSCH Diesel s.r.o and Knorr-Bremse AG. His research interests include lean management, lean 4.0, Industrie 4.0 and the optimization of production systems in general. His e-mail address is j.metternich@ptw.tu-darmstadt.de.