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SEQUENCE SCRAMBLING IN AGGREGATED MIXED-MODEL PRODUCTION LINE MODELING

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ABSTRACT

Global competition and volatile customer demands for individual products lead to shortened product life and innovation cycles and rising numbers of product variants. By manufacturing on mixed-model lines (MML), companies can meet these challenges and produce many variants on one line. To run MML, more frequent planning is required. During early-stage planning, production system constraints, such as buffers and internal supply relationships, must be dimensioned. Therefore, methods like discrete-event simulation can be applied. However, line-modeling parameters are unknown in early-stage planning. Consequently, detailed simulation models cannot be built. For this reason, aggregated modeling approaches are applied. But existing aggregated modeling approaches do not consider MML. Therefore, this paper advances the existing modeling approaches to consider MML and integrates inline variant scrambling effects. This enables the dimensioning of decoupling buffers, as they are necessary to rebuild production sequences. The proposed approach was implemented and applied using an exemplary case study.

1 INTRODUCTION

During the past decade, manufacturing companies experienced enormous changes in their environment. Influenced by global competition and the demand for individually customized products, the number of variants per product increased (ElMaraghy et al. 2012; Wagner et al. 2022). As a result, product life and innovation cycles became shorter, leading to frequent product and production planning (Hopp and Spearman 2011). One strategy to deal with high numbers of variants per product is the establishment of mixed-model lines (MML). These can produce different variants of one product on a single production line but at the same time increase the complexity of production planning.

To deal with the increasing complexity, discrete-event simulation (DES) is a powerful planning and designing tool for complex material flows in production (Skoogh et al. 2012). DES can examine complex systems, which are in the planning phase and do not yet exist. It acts as a decision support for investments in new production lines (Skoogh et al. 2012; VDI 2014). Different technical, system and organizational data are necessary to build a detailed simulation model. In the early planning phase, however, detailed technical data of the production line is not yet available, so detailed simulation models cannot be created either.

A way of using DES with little input data is by applying aggregated modeling techniques, which reduce the complexity of models by abstraction to support manufacturing system design (Pehrsson et al. 2015). Therefore, the aggregation technique needs to take all relevant production line characteristics into account.

Considering a MML, parameters like the throughput, the work in progress (WIP), the lead time, and the production sequence are relevant on a manufacturing system level (Müller et al. 2021). Only if aggregated models take all relevant parameters into account, they can be used to dimension essential production system constraints, such as decoupling buffers between production stages or internal supply relationships. For this reason, we propose an aggregated modeling approach for MML considering all relevant parameters.

The remainder of this contribution is structured as follows. The first section introduces the topic and the initial situation, followed by the second section presenting fundamentals. The third section elaborates on existing approaches for aggregated line modeling and ends with a problem statement for the paper. Section four describes the integration of sequence scrambling into existing aggregated production line models. The results are validated with an application case study in section five. The contribution concludes with a summary and an outlook on future research.

2 FUNDAMENTALS

MML help manufacturing companies to meet today's challenges. For example, they are used in the automotive or electronics sector to handle the increased number of variants and enable an efficient flow-production (Boysen et al. 2009). MML often produce in a given cycle time. This means the stations are arranged alongside a conveyer technology that moves the parts through the line (Boysen et al. 2009), and workers or machines perform pre-defined and repetitive tasks in each cycle.

Companies implement a build-to-order strategy to be able to respond to the variability of customer-specific needs (Fredriksson and Gadde 2005). The planning of MML determines the order sequence of different product variants and is of great importance to meet customer demand (Müller et al. 2021). At the same time, sequencing variants result in challenges for companies. One of these challenges arises from the variants' different processing times, which lead to imbalanced workloads with overloads and idle times for work stations (Alnahhal and Noche 2015). Alternating models with longer and shorter processing times can compensate for this imbalance (Boysen et al. 2009). Another challenge is the increasing complexity of material supply to mixed-model production lines. To keep inventories low, a high mix of variants makes just-in-sequence (JIS) delivery necessary (Meissner 2010).

Various optimization strategies are applied in the planning and simulation of mixed-model lines to circumvent such challenges. März et al. (2011) distinguish three classes of strategies: *level scheduling*, *mixed-model scheduling*, and *car sequencing*. Level scheduling, which originates from the Toyota Production System (Monden 1998), aims to distribute materials as evenly as possible regarding the requirements within the production sequence. Mixed-model sequencing aims to avoid overloading the resources of the flow system. Through precise scheduling of the individual variants at the stations, taking into account variant-related processing times, station lengths, and the cycle time, sequence-related overloads of the stations or workers are to be precisely recorded and minimized (Boysen 2005). Car sequencing applies certain sequence rules, such as prohibiting partial sequences of variants that tend to overload resources. In this way, it attempts to circumvent the detailed recording of mixed-model scheduling.

The sequence planning considers a planning horizon of approximately 0 – 14 days. Resequencing, i.e., changing the sequence after a production plan has been defined, is associated with an increased effort for companies as the availability of parts in the supply chain can no longer be guaranteed (März et al. 2011; Pröpster 2015). Finally, in sequence planning, an optimal mix of variants is to be achieved by considering the customer demand, the processing times, and material delivery. In reality, the task is equal to finding a compromise for the best possible fulfillment of the constraints since a sequence that complies with all restrictions is hardly possible (Meissner 2009).

2.1 Reasons and Measuring Approaches for Sequence Scrambling

A typical setup of mixed-model production lines in industry consists of different stages. E.g. in the first production stage, components are assembled on various pre-assembly lines, which then supply the main assembly line just-in-time. Induced by rework, parallel processes, or different shift models between the stages, the initial order sequence can deviate. This effect is known as sequence scrambling (Meissner 2010;

Müller et al. 2021). Buffers between the lines enable a decoupling and are installed to rebuild the order sequence, see Figure 1.

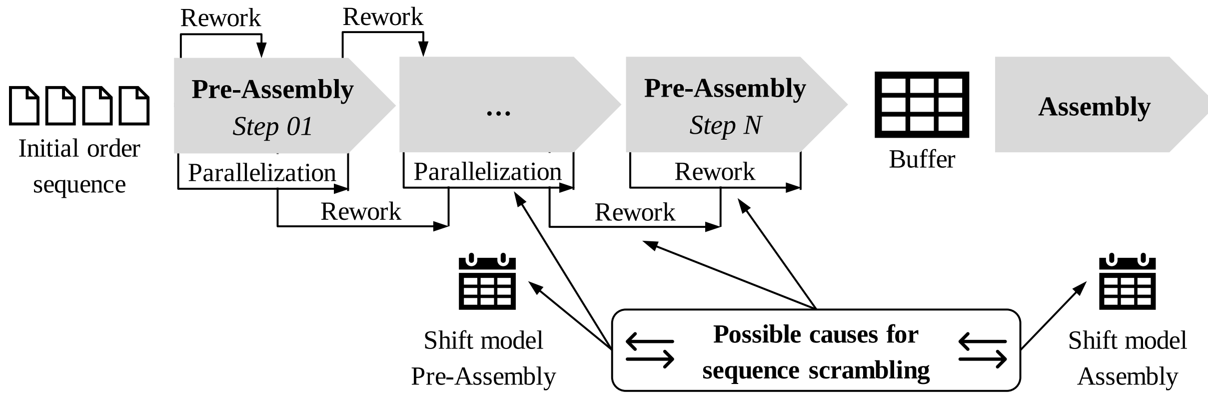

Figure 1: Mixed-model production line following Stauder and Kühl (2022).

As shown in Figure 1, there are several influencing factors for sequence scrambling within the mixed-model production line. These factors can be traced back to operative variability in production lines (Meissner 2009). Causes of operative variability can be process time deviations, availability, random influences, setup, and rework (Hopp and Spearman 2011). Based on this concept, Günthner et al. (2007) identified five main effects on sequence stability which were further elaborated by Meissner (2010): process control effectiveness, material supply reliability, process quality, product planning stability, infrastructure, and layout design.

- Process control effectiveness deals with control errors and restrictions with different shift models influencing the production sequence.
- Material supply reliability requires that production lines' output are merged in one sequence. Problems arise if one production line is not working whereas the other is running.
- Process quality comprises quality locks, rejected parts, and in particular, rework. To rework a part, it needs to be outfed from the production line and infed again after the rework. These events also influence the production sequence stability negatively.
- Product planning addresses technical aspects and customer order changes as well as process time deviations of different variants. This can result in a necessary parallel process, changing the production sequence.
- Infrastructure and layout design influence the production sequence by the selected conveyor technology as well as the production line layout. E.g., parallel stations with different process times cause deviation.

There are different approaches for capturing and measuring sequence scrambling. An essential requirement for measuring sequence scrambling is the product's localization (e.g., most simply by the assignment of sequence position numbers) to compare the planned position in sequence with the position after passing the production line (Meissner 2010). Inman (2003) defines *sequence displacement* (SD) as the difference between the pre-and post-order position in a mixed-model production line. A negative or positive result indicates that a specific product has fallen back or moved forward. According to Meissner (2010), the SD for a sequence element i can be calculated as:

$$SD_i = \ output\text{-}position_i - input\text{-}position_i$$

Furthermore, sequence scrambling can be measured by *sequence adherence* and the *sequence backlog*. The sequence adherence captures the ratio of the number of products that remain in the correct sequence and the number of products that have an incorrect position after the production process. The sequence backlog also captures the deviation between actual and planned sequences, similar to the sequence displacement. The difference is that a specific product is defined, and missing products at the following positions are captured (Meissner 2010).

2.2 The Role of Buffers in Production Systems

Buffers are integrated to reduce the effect of sequence instability by decoupling the stations (Manitz 2005). Decoupling ensures that the sequence can be restored between subsequent plan sequences in the production line. Therefore, a rearrangement or adjustment of the production sequences can be made in buffers (Mayer et al. 2020). In this way, they help to eliminate production-related turbulence effects. For that reason, buffers play an essential role in mixed-model production lines. Since buffers significantly determine the overall behavior of the line, they already must be taken into account in early-stage planning (Bracht and Hagmann 1998). Meissner (2010) summarizes the functions of buffers as follows:

- Decoupling of disruptions
- Bridging distances within the production line
- Resequencing of displaced sequences

This contribution addresses the resequencing function of buffers. For resequencing of displaced sequences within the buffers, the positions of the products must first be determined. Subsequently, the sequence displacement can be calculated as an essential base value for the resequencing process (Meissner 2010). The necessary size of the buffer to rebuild the sequence can be determined based on the degree of sequence scrambling induced by the predecessor production line (Meissner 2010). The sequence scrambling of a production line can be derived from detailed DES models. However, it is not possible to build these detailed DES models in early-stage planning as detailed technical planning is not available yet. Therefore, aggregated line modeling approaches must be applied.

3 EXISTING APPROACH FOR AGGREGATED LINE MODELLING

An established aggregated line modeling approach was published by Pehrsson et al. (2015). The approach aims to aggregate complex production systems into a simple DES model that can be built by standard DES software objects. Therefore, only a couple of input parameters are necessary to set up the model. These are the processing time (PT), the availability, the mean time to repair (MTTR), the maximum work in progress (maxWIP), the average WIP (avgWIP), and the minimum lead time (minLT) (Pehrsson et al. 2015). As output parameters, Pehrsson et al. (Pehrsson et al.) analyze the throughput (TH), the WIP, and the lead time (LT) of a production line. The basic structure of the modeling approach is depicted in Figure 2.

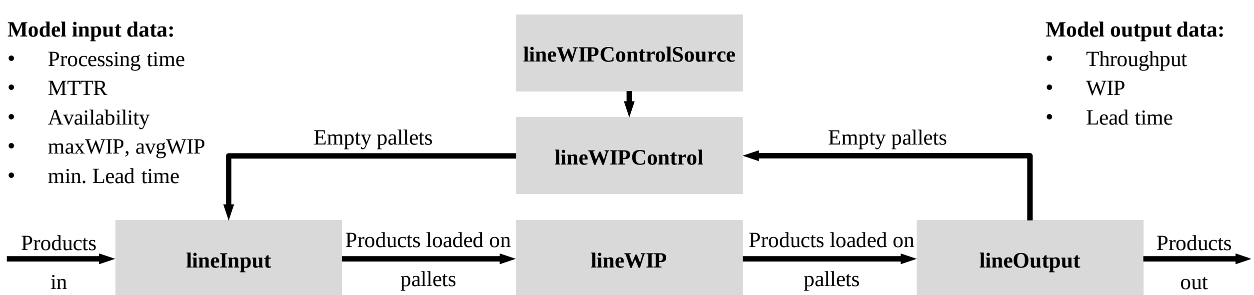

Figure 2: Aggregated line modelling approach following Lidberg et al. (2020) and Pehrsson et al. (2015).

At the beginning of a simulation run, pallets are supplied by the lineWIPControlSource. First, a product arrives at the line input and is loaded on a pallet. Then, the loaded pallet moves to the lineWIP, which is a buffer. After that, the pallet moves to lineOutput where the product is unloaded. Then, the empty pallet moves back to the lineWIPControl to start a new iteration (Pehrsson et al. 2015).

The lineInput and lineOutput control the system variability and the stochastic effects, whereas the lineWIP controls the WIP using a CONWIP based pallet system. Moreover, the lineWIP controls the lead time (Lidberg et al. 2020; Pehrsson et al. 2015). A detailed explanation of the model parametrization is given by Pehrsson et al. (2015). This model is also used and further developed by Lidberg et al. (2020) to integrate variant-specific setup times for the lineInput and the lineOutput objects.

As stated in section two, the production sequence is of great importance for the operation MML. Moreover, the inline production sequence scrambling is an important input parameter to dimension buffers the early-stage planning of production systems as one key reason for buffering is rebuilding the production sequence (Bracht and Hagmann 1998; Müller and Burges 2020). The existing aggregated simulation approaches by Pehrsson et al. (2015) and Lidberg et al. (2020) do not consider this challenge in detail and instead focus on modeling the production line variability and stochastic behavior. The modeling approach shown in Figure 2 depicts that products cannot overtake others, as it happens in real production lines due to parallel stations or rework. Therefore, the input sequence of different product variants matches the output sequence in the existing approach. To address this problem, a further developed modeling approach is necessary, which allows products to overtake others and thereby realize sequence scrambling.

4 INTEGRATING SEQUENCE SCRAMBLING INTO THE EXISTING AGGREGATED LINE MODEL

In order to integrate sequence scrambling, the existing aggregated line modeling approach is used to model the production line characteristics. Then, the sequence scrambling is implemented as described in the following. As shown by Müller et al. (2021) there is an interdependency between the lead time and the sequence scrambling of a product. Figure 3 shows a schematic lead time distribution on the left side. All lead time values are above the minimal possible lead time, which equals the straight processing time. In reality, this lead time cannot be met, e.g., due to longer processing times, downtimes, and rework (Müller et al. 2021). The lead-time variation influences the production sequence as some products are overtaken within the line. These sequence deviations lead to the schematic scrambling profile on the right side of Figure 3. The SD measurement approach calculates the scrambling profile by subtracting the input-sequence position from the output-sequence position (Inman 2003).

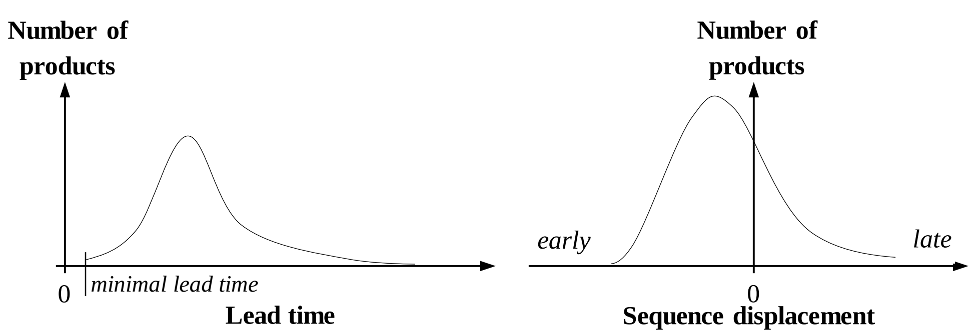

Figure 3: Lead time and scrambling profile following Müller et al. (2021).

When products are, e.g., overtaken, the value of sequence displacement is positive as the products reach the end of the line too late (Müller et al. 2021). In terms of production system stability, a narrow scrambling profile with a mean value of zero is favorable as this means that only a few sequence deviations need to be restored by a buffer (Müller et al. 2021).

In order to integrate sequence scrambling into the existing aggregated line model presented in section 3, it is necessary to enable products to change the production sequence position within the line during a simulation run. Therefore, we propose integrating additional parameters to define the sequence scrambling profile, which affects changing the production sequence position. To define a scrambling profile, statistical distributions can be used. Depending on the distribution type, different new input parameters are necessary (Banks et al. 2010). The schematic approach for sequence scrambling based on a statistical distribution is shown in Figure 4. The input sequence on the left side of the figure is scrambled by applying the statistical distribution in the middle. As depicted in the figure, random values drawn from the range of the pre-defined scrambling profile are used to calculate each products' position in the output sequence on the right side of the figure. For example, product B2 used to be in position six in the input sequence. Due to the sequence scrambling of SD = -3, the product was shifted to position three in the output sequence and thus reached the end of the line three positions too early.

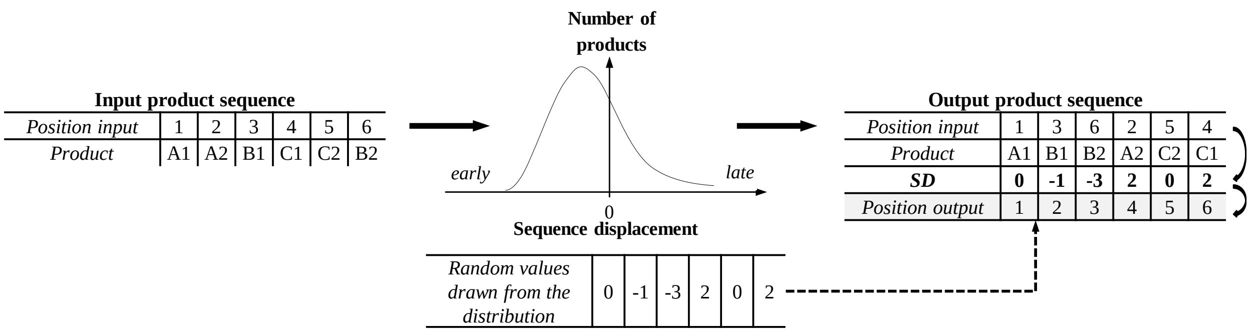

Figure 4: Schematic approach of sequence scrambling based on a statistical distribution.

5 APPLICATION CASE STUDY

In order to model the production sequence scrambling, products need to be able to overtake others within the aggregated line model. In the existing aggregated line model by Pehrsson et al. (2015), products inside the line are represented by the lineWIP object. This object was originally implemented as a first in first out (FIFO) buffer object and suggested to be a storage object for non-FIFO lines (Pehrsson et al. 2015). However, a production line with products overtaking others within the line tends not to be a FIFO line, which leads to the lineWIP being implemented as a storage object (lineWIPscrambl) in our approach, see Figure 5. Apart from the storage object, we use the same objects and parametrization as published by Pehrsson et al. (2015). Figure 5 visualizes the implementation of the developed approach in Plant Simulation.

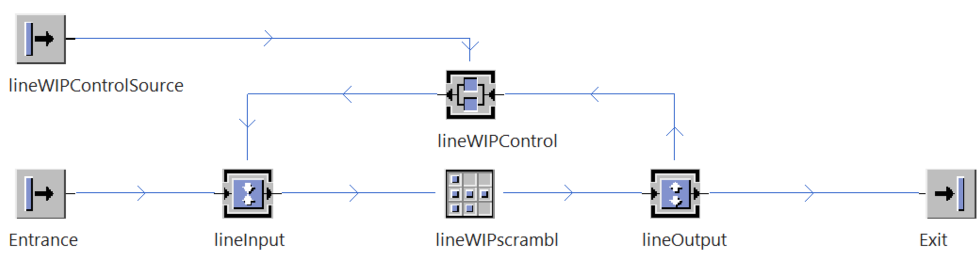

Figure 5: Implementation in Plant Simulation.

We describe the effect of scrambling based on an exemplary normally distributed scrambling profile based on the two input parameters: average Scrambling (avgScrambling) and maximum scrambling (maxScrambling). These two parameters can be used to define the exemplary normal distribution with a mean μ = avgScrambling and an assumed variance of σ^2 = maxScrambling/2.

When a product arrives at the lineWIPscrambl a random scrambling value (SV) is drawn from the normal distributed scrambling profile. Then the product is moved to the inventory inside the lineWIPscrambl object. Within the lineWIPscrambl object, an inventory list contains different information for each product. Firstly, the list contains the planned removal time from inventory, which equals the minLT minus two times the processing time as suggested by Pehrsson et al. (2015). Secondly, a position value is calculated by adding SV multiplied by the processing time to the planned removal time from inventory. Every time a product enters or leaves the lineWIPscrambl object, the inventory list is sorted ascending by the position value. The first product of the inventory list can then be removed from the inventory if the planned removal time is reached. By repeatedly sorting the inventory list, products can overtake others and, consequently, scramble the input production sequence.

For the exemplary application of the approach, we used the input data displayed in Table 1 to parametrize the simulation model. The fourth column, *ProductMix*, contains a table with two different product variants (Variant_A and Variant_B) and the take rates for each variant (Variant_A: 40 % and Variant_B: 60 %). In order to compare the influence of sequence scrambling, we set up three scenarios. The first scenario (Scenario_01) does not include scrambling and thus represents the existing aggregated line model by Pehrsson et al. (2015). The second scenario (Scenario_01) does include scrambling as the maxScrambl equals a SD of 100 and the avgScrambl a SD of zero. The third scenario (Scenario_03) also includes scrambling but with a reduced maxScrambl equal to a SD of 20 and an avgScrambl equal to a SD of zero. Apart from the two scrambling parameters, all input data is the same for all scenarios. We simulate a duration of 10 days for each scenario. The goal of these three scenarios is to show normally distributed sequence scrambling profiles as pre-defined by the input parameters for Scenario_02 and Scenario_03.

Table 1: Exemplary input data for the model.

inputScenario [Text]	**lineMTTR** [mm:ss.ms]	**processingTime** [mm:ss.ms]	**lineProductMix** [Table]	**minLeadTime** [mm:ss.ms]	**lineAvailability** [%]	**maxWIP** [pc.]	**avgWIP** [pc.]	**maxScrambl** [SD]	**avgScrambl** [SD]
Scenario_01	5:00.0000	1:00.0000	ProductMix	4:30:00.0000	95	850	550	0	0
Scenario_02	5:00.0000	1:00.0000	ProductMix	4:30:00.0000	95	850	550	100	0
Scenario_03	5:00.0000	1:00.0000	ProductMix	4:30:00.0000	95	850	550	20	0

The simulation results are visualized and analyzed based on histograms of the LT, the WIP, and the scrambling profile. Figure 6 shows the simulation results for Scenario_01. The histogram on the left side of the figure displays the LT in seconds on the x-axis based on a bin width of 60 seconds. The y-axis indicates the frequency of each group with a sum of all frequencies equaling 100. The histogram in the middle of Figure 6 displays the scrambling profile in SD based on a bin width of one. The right part of the figure shows the histogram for the WIP in pieces within the line, which corresponds to the inventory in the lineWIPscrambl object. The same visualization is used for the simulation results of Scenario_02 and Scenario_3 in Figure 7 and Figure 8. For Scenario_02 and Scenario_03, only the scrambling parameters changed, whereas all other input parameters remained constant.

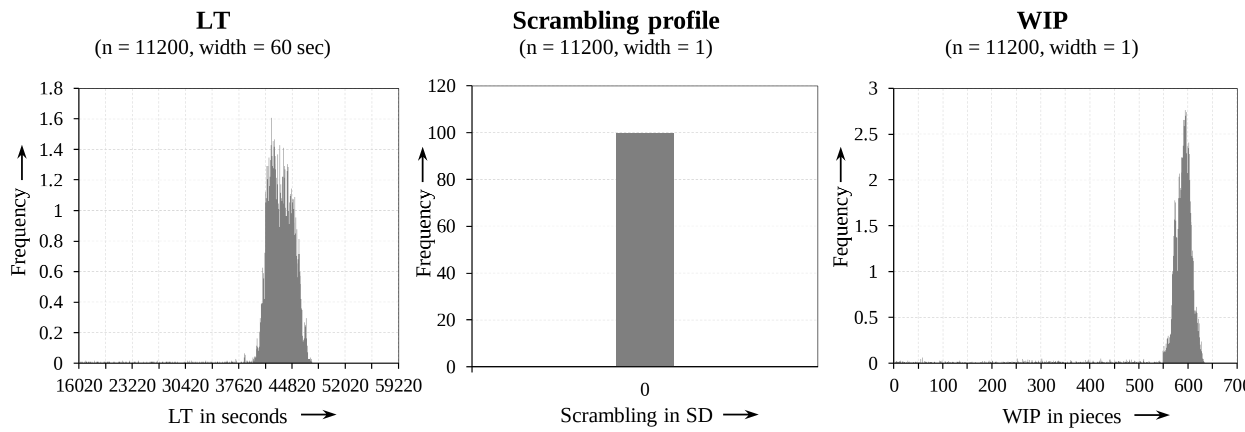

Figure 6: Simulation results Scenario_01.

The goal of the presented approach was to implement a sequence scrambling profile into an existing aggregated line model. Analyzing the scrambling profile of Scenario_01 (in the middle of Figure 6), Scenario_02 (in the middle of Figure 7), and Scenario_03 (in the middle of Figure 8) shows apparent differences. The scrambling profile of Scenario_02 and Scenario_03 follow the pre-defined normal distributions based on the input parameters (see Table 1), whereas the results of Secenario_01 indicate no scrambling. Thus, the goal of implementing sequence scrambling is reached, as indicated in the scrambling profile in Figure 7 and Figure 8 compared to the scrambling profile in Figure 6, which represents the results of the existing approach by Pehrsson et al. (2015).

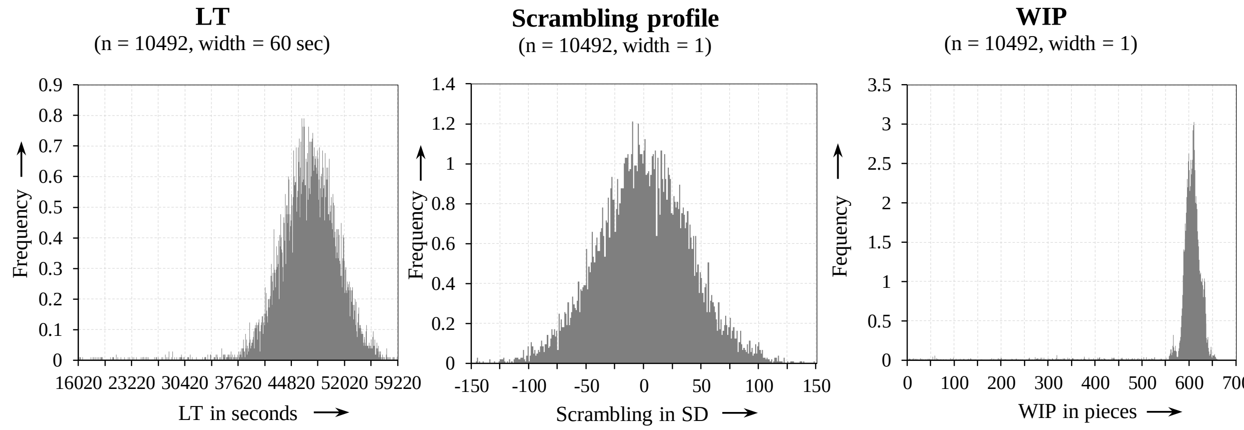

Figure 7: Simulation results Scenario_02.

Sequence scrambling is an important characteristic of mixed-model production lines for the dimensioning of buffers in production systems, as one of the main functionalities of buffers is to resequence displaced sequences. Therefore, the presented approach enables aggregated line models to be used for purposes such as dimensioning buffers between mixed-model production lines.

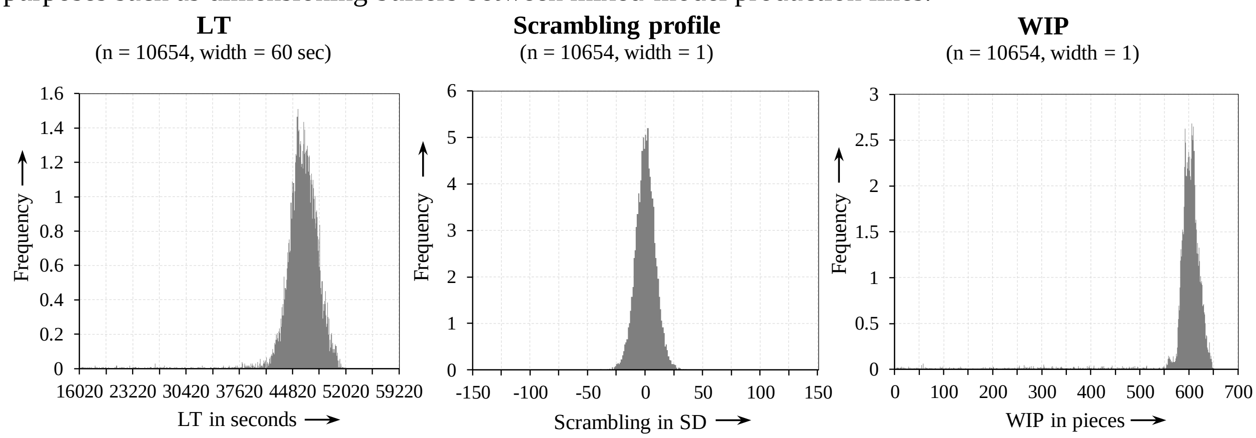

Figure 8: Simulation results Scenario_03.

6 CONCLUSION AND OUTLOOK

This paper describes an approach to integrate production sequence scrambling into the existing aggregated production line modeling technique. Aggregated production line models are used in early-stage planning for DES manufacturing system design since little input data is required, but important system behavior parameters can be derived. An essential task of early-stage planning is the dimensioning of buffers between different production stages. A significant reason for buffering in mixed-model production lines is to rebuild the production sequence, which is necessary to realize the build-to-order principle. In order to integrate the sequence scrambling, a scrambling profile based on a statistical distribution is used to resort products within the production line WIP. A first application case study shows the expected outcomes as the resulting product scrambling follows an exemplary normal distribution.

Further research needs to be done in a detailed validation of the proposed approach in an industrial setting. Moreover, an extensive parameter study needs to further analyze the effects of sequence scrambling on the LT and the WIP. Another research goal is to develop a methodology to derive sequence scrambling parameters (e. g. maxScrambling and avgScrambling) from early-stage planning production line concepts.

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