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EXTENDING SIMULATION-BASED ASSEMBLY PLANNING TO INCLUDE HUMAN LEARNING AND PREVIOUS EXPERIENCE: A SIMULATION STUDY

Maximilian DUISBERG ✉, Michael KRANZ, Verena NITSCH, Susanne MÜTZE-NIEWÖHNER

Institute of Industrial Engineering and Ergonomics, RWTH Aachen University, Aachen, Germany

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Abstract. When using simulation-based assembly planning in the planning phase of designing modern assembly systems, the prospective system behavior should be predicted as reliably as possible by the simulation. For this purpose, personnel-related adjustment periods, such as those related to learning through task repetition should be considered in the simulation model, if employees are later to be involved in the assembly. The learning effect influences the overall performance of the system and can be described by learning curves. The aim of the approach presented in this paper is to increase the prediction quality of simulation models for assembly planning by taking into account the previous experience of the employees. For this purpose, a learning model is integrated into a discrete-event simulation and subsequently verified. The learning model includes the personnel-related learning curve as well as the previous experience of the employees as dynamic parameters. Simulation experiments with three forms of assembly organization were conducted to investigate the influence of learning and previous experience on the dynamic system behavior of an assembly system. The results indicate that assembly systems organized according to the One Piece Flow principle allow for broader, albeit slower, learning compared to row and group assembly.

Keywords: learning models, learning curve, assembly, discrete event simulation, human factors, simulation, industrial engineering.

✉Corresponding author. E-mail: *m.duisberg@iaw.rwth-aachen.de*

Introduction

Modern assembly systems have to meet various demands posed by increasing flexibility needs and shortened product life cycles (Kampker et al., 2013). Despite increasing automation, humans are an important part of modern assembly (Fletcher et al., 2020), not least because of their high adaptability. Hence, attention needs to be paid to factors affecting human performance when planning assembly systems (see e.g. Hopko et al., 2022). However, especially in simulation-based planning, such human factors are often neglected (Baines et al., 2004).

In this paper, it is proposed to integrate human factors in simulation-based assembly planning using Discrete Event Simulation (DES). DES has established itself in industrial practice as a planning tool to predict the dynamic interactions of components in assembly processes (Centobelli et al., 2016; Halim et al., 2020; Li et al., 2019). Baines et al. (2004) have stipulated that the rudimentary representation of humans in simulation is a central reason for inaccuracies and misjudgments in simulation-based assembly planning. They therefore referred to humans as the "missing link" for the further progress of simulation as a planning tool (Baines et al., 2004).

Wang and Abubakar (2017) show in their literature review that, among all human factors considered, the workers' experience is recognized to have one of the highest impacts on the productivity of human-centered production systems.

In the context of new and re-planning of assembly systems in an existing company, it seems useful to take into account the previous experience of the workers with similar assembly tasks. This allows for a better estimation of the system behavior, especially in the more frequent start-up phases caused by short product life cycles (Frey et al., 2011). Furthermore, it allows initial estimations regarding the behavior of assembly systems in which experienced and new workers work together (Duisberg et al., 2022).

Therefore in this paper, a learning model is considered that incorporates not only the learning of a specific assembly task, but also the previous experience with similar tasks. In previous years, several articles have been published describing the integration of human factors in the simulation of assembly or production systems. An overview of publications with this topic was given by Greasley and Owen (2018). Some of the reviewed papers describe incorporating learning models. These approaches will be discussed in more detail in the following paragraphs. In this context it will be discussed whether the integrated learning model and its parameterization have been described in such a way that the modeling can be taken up for further simulation studies. Furthermore, it is investigated whether the consideration of the previous experience of the workers with the chosen models is possible and how it is measured.

Neumann and Medbo (2016) study a parallelized assembly line compared to a conventional serial flow. The modified setup led to longer cycle times. To improve the prediction quality of their simulation approach, the authors integrated a learning model that takes into account the effects of longer processing times and greater learning content in the ramp-up phase. It was assumed that all workers have the same learning behavior and start the process with the same level of knowledge so there is no dedicated consideration of previous experience.

Dode et al. (2016) investigate the effects of the design of an assembly system on employee satisfaction and productivity. The authors consider a fatigue dosing and a learning model in their simulation study. Following De Jong (1957) the model tends towards a lower bound and is described by a power function. An interaction of the human factors is not considered in the model.

Nembhard (2014) examines the efficiency and flexibility of workers in a workplace who are subject to on-the-job cross-training. The study considers a heterogeneous group of workers. The author shows, that a moderate level of cross-training leads to a gain in productivity and outweighs the production losses. But this only applies to a very low number of activities to be learned. The learning model used in this study was not described in a way that allowed a reproduction in this study.

Wang et al. (2013) show in their study the effects of incorporating a learning curve on the performance of individual workers in DES. The consideration of the learning curve serves as a support for the decision which level of task complexity can be learned by workers in an acceptable duration. In addition to the learning curve, the study considers human factors such as cognitive and physical elements. The simulation models are used for the examination of One Piece Flow systems. Their approach leads to a suitable assignment of products and individual workers. But the theoretical basis used for the learning curve is not clearly stated in the publication.

Building on the work of Greasley and Owen (2018), who had reviewed articles in the time period of 2005-2017, a literature review was conducted using the same approach for the years 2017 to 2022.

Among the publications from the period considered that have integrated a learning model are three papers by Abubakar and Wang (2018a, 2018b, 2019). Abubakar and Wang (2018a, 2018b, 2019) consider the change in performance of a worker due to both learning effects from repeated execution of a work task and the age of the worker. The authors show the dynamic calculation for both submodels. The determination of the learning rate in their papers is based on the change in assembly time with increasing age of the workers. However, it does not become clear whether the simulation covers periods that allow to map the change of the age of workers and the models are combined in an unspecified way to determine the output.

Ranasinghe et al. (2018) examine the effects of non-homogeneous learning on the performance in serial production. The authors use the power learning curve model by Dar-El (2000) to calculate the processing time. The results of the study show, that the consideration of different learning rates for individual workers has an adverse impact on the calculated overall performance of the production system.

The relatively large number of publications that integrate a learning model underlines the utility of extending simulation models accordingly. Most papers described here are based on De Jong's learning model and use it in a slightly modified form. In doing so, the parameterization of the model either is based on data from a use case or is not explained in detail. None of the existing implementations in the simulation takes into account the previous experience of the employees to determine the learning curve.

The available papers on learning models in simulation describe modeling approaches that use a few and easily collected parameters, such as age, to model worker characteristics. In simulation-based planning, however, the goal is to achieve the highest possible prediction accuracy, while at the same time keeping the data collection effort low.

Since no implementation of a learning model incorporating previous experience was found in the literature review, in this paper, a learning model is integrated into a DES that considers not only the experience with the specific assembly task, but also the previous experience through similar assembly tasks as a dynamic parameter. For this purpose, existing learning models are briefly described, and on this basis, the modeling used in this paper is explained in Section 1. The section concludes with an adaption and parametrization of the selected learning model for application in simulation-based planning. In Section 2, the implementation of the learning model in the simulation models is further elaborated. Subsequently, Section 3 describes the conducted simulation experiments and the verification of the learning model. The results illustrate the differences in system behavior when considering learning and previous experience in assembly simulation in different ways. Finally, the potentials and challenges of this approach are discussed and an outlook on topics for further research is given. The paper extends the work by Duisberg et al. (2022) originally presented in the conference ESM® ‘2022.

1. Learning model derivation

Amongst the first to formulate mathematically employee effects in the context of production was Wright (1936; see also Liebau, 2002). While studying the production of airplanes, he found that the effort required for production (factor input of capital, labor, etc.) decreases by a constant percentage for each doubling of the output quantity (Liebau, 2002). Based on this, the derived following formula (1) for process time was described in Jeske (2013):

$$\overline{t_n} = n^{-k} \times t_1. \tag{1}$$

The number of repeated executions of the work task is represented by the variable n and thus, t_n describes the calculated processing time for the n-th repetition. The factor t_1 denotes the processing time of the first execution.

The most criticized aspect of Wright's approach is the underlying power function, which postulates an unbounded progress leading to infinitesimal processing times (Liebau, 2002). To address this problem, De Jong's model accounts for a learning progress bounded by an irreducibility M in a range of values 0 ≤ M ≤ 1. While the duration corresponding to proportion M is the long-term limit of the model, the duration corresponding to proportion 1-M is reduced proportionally to n by repeated execution of the task and the associated practice (De Jong, 1957):

$$t_n = t_1\left(M + \frac{1-M}{n^k}\right). \tag{2}$$

The model of De Jong is applied in several simulation studies (see Abubakar & Wang, 2018; Neumann & Medbo, 2017). It may be assumed that this kind of modeling approach is suitable for simulation purpose but does not incorporate any kind of previous experience.

The learning curve model according to Ullrich (1995) is one of the few that takes into account the previous experience of workers. Ullrich identified four requirements for learning curve models based on a comparison of several learning curve models: (A) a distinction between a time portion that can be reduced by learning and a fixed limit value, (B) an asymptotic approximation of the learning curve to the limit, (C) a constant rate of change according to Wright's linear hypothesis (Wright, 1936), and (D) the consideration of previous experience of the worker (Ullrich, 1995).

Since Ullrich uses De Jong's modeling as a basis for his model, it can be assumed that this kind of modeling approach is suitable for the intended simulation purpose.

Ullrich's model (3) takes into account the previous experience of a worker using the quantity B as the number of work executions already performed. The previous experience was originally introduced by the Stanford University (Ullrich, 1995; Liebau, 2002) and was developed to predict the productivity advantage of factories that had already produced a similar product. The factor increases the output quantity n arithmetically and thus shifts the learning curve by B executions (Ullrich, 1995):

$$t_n = t_\infty + \left(t_1 - t_\infty\right) \times \left(n + B\right)^{-k}. \tag{3}$$

Ullrich defines t_∞ for the irreducible execution time to limit the reduction of the function. Considering the application in the simulation and the usually available data, the factor t_1 is described by the irreducible time multiplied by a reduction factor. With (4) results the final formula (5) for this modelling approach (Ullrich, 1995):

$$t_1 = M \times t_\infty; \quad (4)$$

$$t_n = t_\infty + \left(\left(M-1\right) \times t_\infty\right) \times \left(n+B\right)^{-k}. \quad (5)$$

Jeske (2013) shows based on a series of learning experiments that the learning model according to Ullrich (1995) achieves a high coefficient of determination in the description of relative learning curve progressions. Based on his studies, it seems reasonable to choose the extended power function according to Ullrich in the context of prediction of learning curves in simulation models.

The approach allows to estimate the behavior of an assembly system employing experienced workers during the ramp-up of a new product and the employment of workers with different levels of experience.

Since there are usually no physically existing assembly systems available in the planning phase to collect data for the parameterization of the learning model, suitable parameters are derived from the relevant literature and described in the following.

In order to use the formula defined above in a simulation model, the following parameters need to be defined:

t_∞ – irreducible time;
k – learning rate;
t_1 – time of first execution;
M – reduction factor;
B – previous experience;
n – repetition;
t_n – calculated time.

The irreducible time t_∞ of an activity must be assumed to be given from the working plan on which the assembly planning simulation is based. This is commonly a value calculated by methods-time measurement (MTM) or a similar procedure. Since this marks the basic time needed for a work task, it will be named the basic Time t_g.

The learning rate k is an individual factor, which depends on the worker and the work task. As the value is a highly personal value, it cannot be assumed that such data would be available for a planning project. In addition, both Jeske (2013) and Kuhlenbäumer (2020) point out, that it is difficult to determine this parameter precisely. Instead, it will be considered as a fixed value, which is deemed suitable in the context of a planning approach. Wright (1936) shows in his study that the value is usually around 80% which leads for x^k to k = 0.32. De Greiff (2001) shows that this value has been confirmed as the most frequent mean value in a number of 15 studies conducted by the Manufacturing Technology Laboratory of the University of Duisburg.

The initial value t_1 is particularly easy to determine when deriving a learning curve from a series of experiments. De Greiff (2001) chooses a complex procedure for this, which requires a precise knowledge of the performed task, so that in the context of simulation the application of Ullrich (1995) is used instead. For the reduction factor:

$$M = t_1 / t_g. \quad (6)$$

Ullrich determines values between 1.41 and 3.34 with an average value of 2.12 for which he evaluates learning experiments of the Manufacturing Technology Laboratory of the University of Duisburg (Ullrich, 1995). *M* is assumed as 3.34, so that the resulting learning curve tends to overestimate the additional effort required by the worker. Since this assumption represents a safe estimate, it will be used in the further process. This results in the following formula for implementation in the simulation:

$$t_n = t_g + \left(2.34 \times t_g\right) \times \left(n + B\right)^{-0,32}. \tag{7}$$

2. Application in DES

For the application in DES, the presented learning model will be integrated into existing assembly simulation models using the FlexSim® simulation software. First, the functionality of the selected simulation models is presented and, on this basis, a transfer of the learning model to the simulation is developed.

When modeling the assembly systems, the process of assigning and processing a work order was represented in a process flow, which in its logic is comparable with a colored Petri Net. Each worker is represented by a 3D visualization in the virtual assembly line and by a token in the process flow. An example for a process flow is shown in Figure 1.

Both elements of the representation of one worker are referencing and influencing each other. The control flow to represent the worker behavior is generally directed from the token to the 3D model, since the logic was primarily modeled in the process flow. However, when aspects can be more meaningfully represented in the 3D world, like the way time needed to move from one workstation to another, a reverse influence occurs.

The representation of the processing time also takes place in the process flow. According to the organizational form of the assembly system, a token is assigned a work task and a workstation.

Since the learning model describes a processing time that can be determined for a specific work task, worker and point of time in the simulation, the processing time cannot be calculated before the assignment is complete. Considering the learning model, the processing time must be recalculated for each repetition. For this purpose,

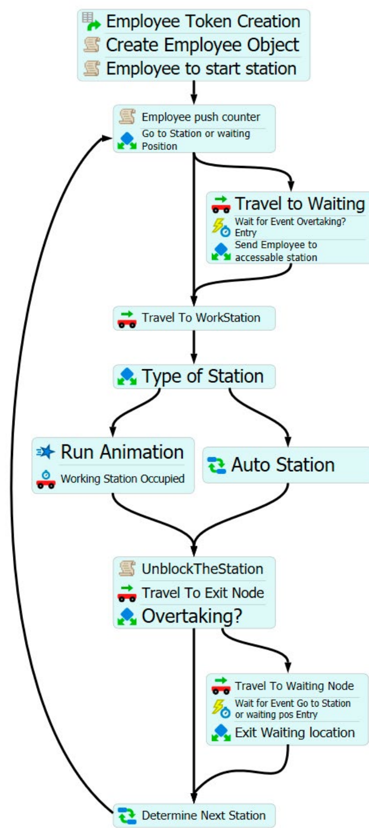

Figure 1. Process flow of the assignment of tasks to and the processing by workers, mapped in FlexSim® software with the example of the One Piece Flow

the corresponding formula is added to the code block responsible for modeling the processing time in the process flow.

When a token reaches the point "Working Station Occupied", the processing time is calculated, and the worker starts processing the task. To calculate the processing time considering the learning model, the formula (8) must be converted into a form suitable for the programming environment, with:

t_g – *basicTime*;
k – *learningRate*;
t_1 – *TimeofFirstExecution*;
M – *reductionFactor*;
B – *previousExperience*;
n – *repetition*;
t_n – *calculatedTime*;
a^b – *pow*(a,b).

$$calculatedTime = basicTime + \left(\left(reductionFactor - 1\right) * basicTime\right) * \\ pow\left(repetition + previousExperience, -learningRate\right). \tag{8}$$

For the calculation, values must be assigned to the variables. The empirically determined values must be provided for the variables *learningRate* and *reductionFactor* to improve the applicability of the learning model. The variable *basicTime* can be set to the target time belonging to the work order and should be provided as input data to the simulation model. To determine the number of repetitions and the previous experience, a dynamic list in the simulation environment is used. Here, the workers are matched with the executed work tasks, so that the variable repetitions can be determined easily. Table 1 shows an excerpt of the dynamic list used for the experiments described in the next section. As the work tasks are always assigned to a fixed workstation, these are used for referencing the repetitions.

The value of the variable *previousExperience* can be summed up by repetitions of all similar work tasks. In this case it is assumed that all work tasks in the assembly process are similar enough so that work tasks are not selected by similarity in order to simplify the calculation. Therefore, the repetitions of all previously performed work tasks are taken into account when calculating the experience. In the list, this is done by summing up the total number of work tasks in one column (see Table 1). Finally, the number of repetitions of the work task is increased at this point to record the new repetition.

Table 1. Dynamic list for tracing the repeated tasks by worker during simulation

	Employee_1	Employee_2	...	Employee_m
WorkTask _1	3	5		10
WorkTask _2	5	13		11
WorkTask _3	7	8		8
...				
WorkTask _n	9	12		7
Sum	24	38		36

3. Simulation experiments

Experiments with simulation models of different forms of assembly organization were used to investigate the effects of the learning model taking into account previous experience. In particular, the effect of the variable *B* for the previous experience was examined more closely.

For the experiments three assembly organization forms have been selected, which exhibit differences in two aspects: the flow of materials through the assembly process and the allocation of tasks to workers, affecting how they interact with each other. It is to investigate whether different repetition patterns caused by the forms of assembly organization lead to dynamic effects that this study aims to investigate. The selected forms are group and row assembly, as well as the One Piece Flow (OPF).

In group assembly, groups of workers process the assembly objects by carrying out a series of work steps, e.g. the complete wiring of a machine. While the assembly objects remain in one place during the entire assembly process, the groups move between the assembly objects. Several groups of specialized workers are needed to complete the assembly of a product (Eversheim et al., 1981).

In row assembly, the arrangement of workstations corresponds to the processing sequence for manufacturing the product. The workers usually work at one workstation and repeat the same tasks for each product (e.g., laying individual cables).

In OPF, the work stations are also arranged according to the processing sequence. Worker and assembly object move through the assembly system together. The worker must therefore perform several work steps and may not be as specialized as the workers in a group assembly system. On the other hand, this can lead to greater flexibility in the assembly system (Arzet, 2005).

Figure 2 provides an overview of the flow principle of the assembly organization forms under study. The flow principles of the selected assembly organization forms are depicted as adaptation from Eversheim et al. (1981).

The three forms differ in terms of both the flow of materials and the organization of the assigned coworkers as pointed out above. For a more comprehensive understanding

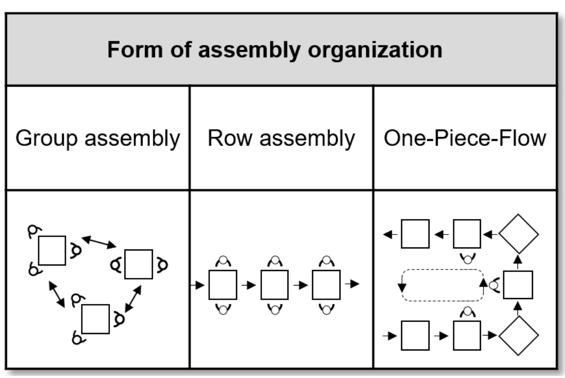

Figure 2. Flow principles of the selected assembly organization forms according to Eversheim et al. (1981)

of assembly organization forms and a detailed development of the simulation models that represent them, please refer to the detailed explanation provided by Duisberg et al. (2021) in their work.

To ensure comparability, all three models were formulated based on the same work plan. The work plan specifies which work steps have to be completed and the duration of each step in the assembly of a product. To increase the transferability of the results, a reference work plan was used, which was derived from five work plans for different types of assembly organization provided by companies from several industries. The distributions of the processing times and the probabilities of different types of executions (e.g. joining, handling or testing) were derived from these work plans. The distribution of the time data was described by exponential functions for each type of execution. These functions were used to generate random values for the reference work plan. The reference work plan comprises 100 work steps and a total duration of 370 minutes and can be utilized for comparable simulation studies of the three forms of assembly organization under consideration.

In all assembly systems, 20 workers are used for assembly. The simulation experiments were carried out for a duration of 2000 hours each, which corresponds to one year of working time. Seven scenarios were considered for the three assembly organization forms. Each scenario was repeated 200 times.

In the first scenario, the learning model is not used to calculate the processing times. This scenario serves as a reference for the further tests. In the second scenario, the learning model without previous experience B is used. This scenario is used to verify correct operation of the model and to make comparisons with scenarios incorporating the previous experience. In the third scenario, a fixed previous experience is considered. The value for B is initially set to 200 for all workers and is maintained during the simulation experiments. This scenario thus picks up on Ullrich's model.

Scenarios four to seven make use of the simulation's ability to dynamically change input values. In these scenarios, the previous experience is taken into account. The repetitions of other, similar work steps in the assembly system are included in the determination of the learning curve for a specific step. The previous experience thus increases dynamically up to a previously defined limit. The limit values of the individual scenarios can be taken from the overview of the simulation experiments in Table 2.

To record the results, the processing time for each worker at every workstation was documented in a list. The values were normalized by dividing them by the *basicTime* t_g. Then, the processing times per repetition were averaged over all workers. The result is a numerical series of values for each scenario.

Table 2. Scenario configuration for the simulation experiments

	Scenario 1	Scenario 2	Scenario 3	Scenario 4	Scenario 5	Scenario 6	Scenario 7
Learning Model	off	on	on	on	on	on	on
Previous Experience	off	off	fixed	dyn.	dyn.	dyn.	dyn.
Limit	0	0	200	100	200	400	5000

4. Results

Simulations conducted with and without the learning model were compared, to examine whether the models exhibit the desired behavior. When the values determined according to the procedure described above are represented graphically, a curve with a characteristic progression for learning models is obtained for the second simulation run and a straight line for the first simulation run. Figure 3 shows the results for the One Piece Flow simulation model.

For further verification, the formula values for formula (8) were calculated independently of the simulation and inserted in the diagram. For better readability of the figure, the values of the data series from the second simulation run were shifted down by 0.1. The results show that the model behavior suitably reproduces an empirically determined learning curve.

After it has been verified that the simulation model reproduces the behavior of the underlying theoretical model, the comparison of the assembly organization forms were carried out. The analysis of the data showed only little differences between the assembly organization forms. When the results of the second scenario for all three assembly organization forms are depicted in a diagram as shown in Figure 4, the curves show a course that follows the typical course of a learning curve.

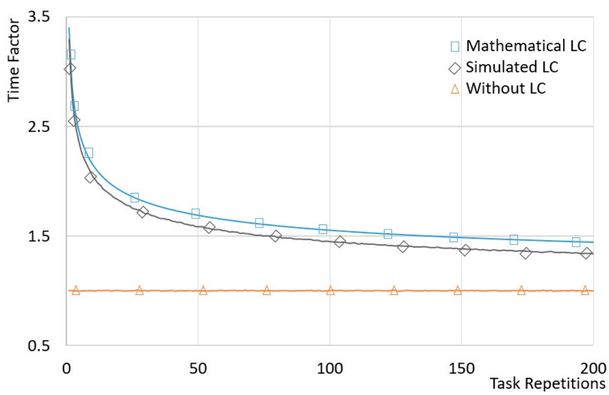

Figure 3. Comparison of formula values and simulation values with and without learning model

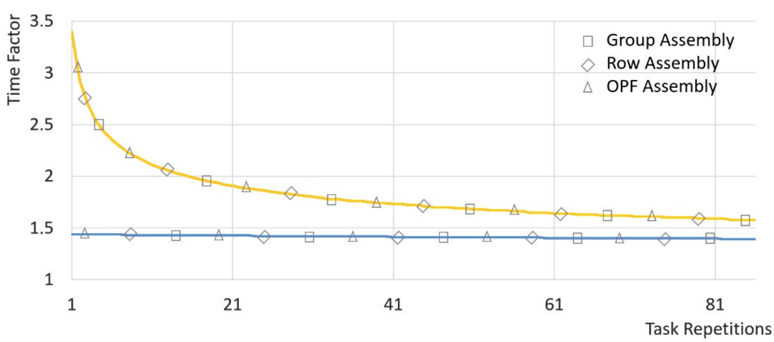

Figure 4. Comparison of the learning curves for scenario two and three

Furthermore, the figure shows that the curves are congruent. This indicates that the learning process takes the same course in the different forms of assembly organization.

In scenario three, a fixed value for previous experience is used. According to the explanations of Ullrich (1995), a consideration of the previous experience by the parameter *B* shifts the learning curve by the number of *B* repetitions to the left. For this purpose, an experiment was conducted with a fixed value for $B = 200$. The resulting curve starts with clearly lower values for the first repetitions, but then drops very little. This behavior can also be observed for scenario two for high repetition numbers. The results for scenario three were also identical for all three forms of assembly organization.

The behavior of the assembly organization forms when a dynamic previous experience was taken into account was then examined in more detail in scenarios four to seven. The limits for the previous experience *B* were varied as follows to examine the value range for *B*. Contradictory statements can be found in the relevant literature, which are difficult to verify. While some authors mention values for *B* of up to ten, other authors argue that significantly larger values for *B* are also possible (see e.g. Liebau, 2002; Ullrich, 1995).

In order to investigate the effects of the *previousExperience* parameter *B*, simulation experiments were carried out for the different assembly organization forms in which *B* was limited to different values according to Table 2. At the beginning of the simulation run, the value for *B* was always zero.

Initially, it can be determined that the learning curves of the models for different forms of assembly organization behave in the same way in these experiments. The curves for the four scenarios of a model start at a similar level. With increasing repetitions, the curves of the scenarios with higher thresholds for previous experience then drop further, resulting in lower repetition times. This is identical for all scenarios.

The comparison of the results of the three forms of assembly organization for scenarios four to seven (Figures 5–7) shows that the curve progressions for the assembly organization forms of row and group assembly are almost identical (Figures 5, 6). The learning curves from the experiments for the One Piece Flow presented in Figure 7, on the other hand, start at slightly higher values and the curve progression is not as steeply sloping in the following. While in the case of the row and group assembly all curve progressions are almost parallel

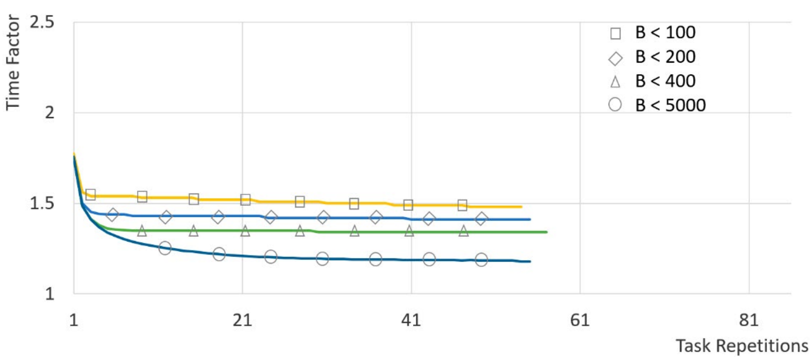

Figure 5. Results for scenario four to seven of the group assembly

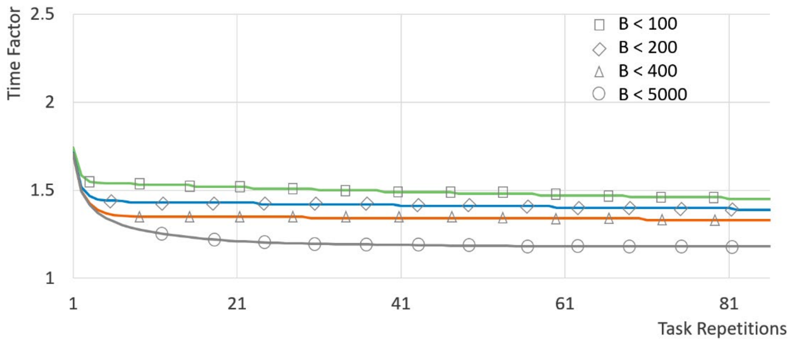

Figure 6. Results for scenario four to seven of the row assembly

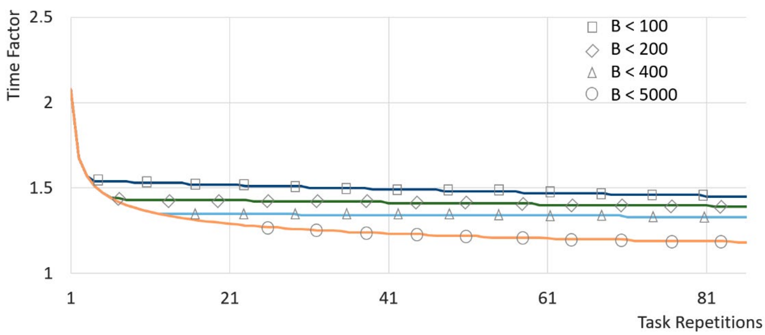

Figure 7. Results for scenario four to seven of the One Piece Flow

after 40 repetitions, in the case of the One Piece Flow the curve for scenario seven drops more steeply over the entire observation range than that of the other scenarios.

This difference can be explained by the different organizational principles. Since the workers in One Piece Flow go through all work steps exactly once before a step is repeated, the repetitions of all steps are identical, which leads to a constant increase in previous experience.

In the other two forms of assembly organization, this fixed sequence of processing steps is not necessary. Workers repeat individual steps much more frequently and skip other steps altogether. Since the learning curves shown here are determined by averaging over all steps and omitting any repetitions that have not been performed, the more frequent repetition of individual steps leads to a sharper drop in the learning curve. This results in greater specialization with respect to the individual worker.

4. Discussion

The objective of this work was to increase the prediction quality of simulation models for new design and redesign of assembly systems by taking into account the previous experience of the workers.

The implementation of a learning model presented in this paper extends the approaches discussed at the beginning by incorporating an additional factor to consider previous experience. A task-based approach was taken in the implementation, so that the number of repetitions for each work task is recorded and counted for each worker. This also makes it possible to represent the differences in learning levels of different workers resulting from a task distribution. Compared to other models, the model incorporates an additional dynamic parameter and its changes can be tracked over the course of the simulation run.

The values used to specify the parameters of the learning model are based on empirical research instead of a specific use case. Also the work plan, which is part of the input data for this experiments is based on data from several assembly organization forms. This approach offered the potential to increase the transferability of the model to different case studies, since the database used to determine the parameters covers a broader range of applications overall. The selected parameters and data for the work plan were mainly collected in the German-speaking area. Before applying the model in other regions, it should be checked whether it is transferable.

When comparing the model used with the current research on learning models, there are learning models that use several parameters to capture the previous experience of a worker in more detail. Thus, the learning situation can be captured more precisely, which allows for a more accurate mapping of the learning progress. For this, we refer to the studies of Kuhlenbäumer (2020) as an example. In comparison, the selected simple model used in this paper can only provide a less precise mapping of the learning progress based on experience. However, for the more elaborate models, a lot of information about the learning situation and personal information about the workers must be available, which is why they are generally less suited to be applied in the planning of assembly systems when this detail of information is rarely available. Furthermore, due to data protection concerns, these data are often not allowed to be used for simulation-supported assembly planning in German companies.

The results of the experiments show that the learning effects that occur during the repeated execution of work tasks can be reproduced in the simulation. The different results for different assembly organization forms show the advantages of the dynamic modeling of previous experience. On the system level, for example, work organization can lead to positive effects if the level of experience of the workers is homogeneously distributed by organizational matters and thus waiting times can be avoided. At the employee level, certain effects, such as specialization and task variety, can be further investigated using this modeling.

In the presented application of the model, it was demonstrated how this experience parameter may be determined inductively by simulation runs. It is possible to first simulate an existing assembly system to determine the previous experience of the employees and then transfer this data to a new assembly system to be planned. Thus, the often difficult data collection can be avoided. A comparable procedure has already been described by Kranz et al. (2021) and implemented in a simulation study with good results. On the other hand, when using this model, it must be noted that the approach of dynamically adapting the previous experience based on similar assembly steps performed during a simulation run represents an extension of Ullrich's model. It must be verified in the respective use case whether this modeling is suitable for the assembly system under consideration.

Conclusions

The aim of this paper was to investigate how the experience of workers can be taken into account in a simulation model for planning assembly systems. For this purpose, current implementations of learning models in simulation studies were first examined. A suitable model was derived from the literature on learning curves. The model of Ullrich (1995), which is based on the model of De Jong (1957) and frequently used in simulation studies was adapted. The model parameters were specified on the basis of empirical studies.

The simulation models of assembly lines according to three assembly organisation principles were extended by the learning model. It was shown that this extension leads to a change of the simulated processing times, which corresponds to the collected learning behaviour of workers in the assembly context.

The previous experience of the workers in similar assembly tasks was taken into account in the simulation modeling. This resulted in a shift of the learning curve that reflects the shorter initial execution times and faster approach to basic time by experienced workers as described by the learning model.

The application of the learning model to three forms of assembly organization in seven scenarios enabled the in-depth investigation of the interactions between learning effects and organizational principles. The influence of the learning effect on the dynamic system behavior of an assembly system, as well as the interaction of the work organization with the learning model were illustrated in the simulation experiments presented here. It was shown that the use of previous experience as a dynamic parameter in assembly simulation has a differential impact depending on the form of assembly organization. For the simulation-based planning of assembly systems, the modeling can be used to achieve a more realistic representation of the system and a more sophisticated prediction of the dynamic behavior. This can be the case in the ramp-up of new assembly systems or when new products are produced in an existing assembly system. For this purpose, the model parameters can be specified for the respective use case. Furthermore, it must be determined in the specific application case which other activities in the work system are worth considering in order to determine the level of previous experience.

Future research

In order to improve the simulation-based planning of assembly systems, the mapping of previous experience as an important parameter needs to be further investigated.

Further simulation studies with concrete use cases need to be conducted to validate the model and to investigate the suitability for prospective use in the planning phase. In a next step, methods can be collated and tested so that the parameters taken from the literature in this paper can be determined for specific operations.

Future research should especially be dedicated to the empirical determination of previous experience for different task types. The results of this paper show that incorporating previous experience in the simulation can lead to different results and might increase the quality of simulation models. For the further development of this approach, an empirically supported assumption could be made for the parameter *previousExperience*, especially for the use case of simulation-based replanning of work systems, which can be adjusted with increasing degree of specification of the planning.

Furthermore, most simulation studies investigate the effects of one human factor on the assembly system. In some cases, changes in human factors are collected as an additional model output. Future simulation studies should deal with the partly interacting influences of several human factors to better reflect realistic production conditions. For this purpose, dynamically modeled human factors, as it was done with the learning model presented here, are needed and have to be combined in a meaningful way to better represent the different influences of the human as a complex part of the assembly system.

Finally, the simulation-based planning of assembly and other industrial processes is taken to a new level by the recent development of the industrial metaverse. This extended modeling aims at increasing the quality of planning by a holistic view of production systems. Especially in case of assembly systems, this can only be achieved if the workers, as an important part of each work system, are also represented in sufficient detail.

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