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Finding the proper level of detail to achieve sufficient model fidelity using FlexSim: An industrial use case

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Abstract

Discrete-Event Simulation (DES) has established itself as an appropriate instrument for optimizing production facilities in the manufacturing industry, enhancing the overall production system performance and therefore ensuring competitiveness concerning today's difficult market conditions. DES supports decision-making by providing model-based system analyses for given objectives and obtains meaningful and verifiable results. Because high-fidelity modelling is always a time-consuming and therefore expensive task, the necessary level of detail of a simulation model is an important question to answer. Therefore, the goal of this work is to examine the different levels of detail of a series of models created for a complex industrial production system utilizing the FlexSim simulation environment. First, an iterative modelling approach, starting with the development of a low-detail model, followed by the creation of further refined models with higher fidelity, is presented. A qualitative fidelity comparison between the models is stated using 4 fidelity dimensions. Furthermore, the necessary level of detail for a given accuracy target is evaluated by a comparison between simulated and real production system throughputs during model validation. Finally, achieved production system optimizations based on experiments using the adequate model are presented. Despite the large variety of different production environments, similar use cases may profit from the findings presented in this work.

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1. Introduction

Due to its applicability for complex systems that are characterized by the involvement of multiple different entities and sequences of triggering events that determine the systems behavior over time, Discrete-Event Simulation (DES) has found a broad area of application in industrial process optimizations, especially in the areas of manufacturing line optimizations and intralogistics (e.g., [1, 2]), supply chain simulations (e.g., [3, 4]) and patient flow and layout optimizations in the healthcare sector (e.g., [5, 6]). Depending on given project goals and objective functions – like shortening cycle/lead times, maximization of throughput with restricted resources, elimination of bottlenecks within production systems, cost minimization, increase of equipment/worker utilization, and so forth [7] – setting up a representative and meaningful model can be time-consuming and therefore expensive [8]. Furthermore, additional model details usually increase the computational complexity and lead to a longer computation time for a simulation run [9]. Considering this fundamental trade-off problem between effort invested in creating a model and the resulting model fidelity [10] and

2212-8271 © 2023 The Authors. Published by Elsevier B.V.

This is an open access article under the CC BY-NC-ND license (https://creativecommons.org/licenses/by-nc-nd/4.0) Peer review under the responsibility of the scientific committee of the 33rd CIRP Design Conference 10.1016/j.procir.2023.02.192 computational efficiency, one of the main challenges is to find the adequate level of detail for the generated DES models to be representative and meaningful. In some cases, coarse models, built in a short amount of time, can be sufficient to accomplish the simulation project's goals, while in other scenarios, a detailed reflection of the real system and its behavior is necessary to achieve accurate simulation results.

Therefore, this paper utilizes an iterative modelling approach, starting with the development of a coarse low-detail model of the examined system, followed by incremental model refinement loops. The goal is to achieve the required simulation accuracy with a minimum of modelling effort invested. The approach is applied in a research project conducted with a company partner from the automotive supply industry. The contribution of this work are the simulation accuracies for the created models with different levels of detail during the refinement loops, obtained in the model validation process. The validation is done using actual production data from the physical system. Furthermore, the respective level of detail of each model is qualitatively characterized using 4 fidelity dimensions. The modelling was done utilizing the FlexSim DES environment (Version 20.2.3).

The remainder of this paper is structured as follows: In section 2, related research activities concerning fidelity of DES models are mentioned. Section 3 states the applied research method, followed by the description of the examined industrial use case in section 4. Section 5 describes the generated models and compares the different levels of detail and the resulting model fidelity qualitatively. In section 6, the results in form of the quantitative deviation of production throughput between the established models and the validation data gathered from the physical production system are stated. Furthermore, additional optimization experiments for a planned extension of the production system based on the chosen simulation model are described. Section 7 contains final conclusions, further research demand and a short outlook on future work in the ongoing research project.

2. Related Work

Because the overall model fidelity is dependent on different dimensions of the particular application domain and the defined simulation purpose, there is no universal approach of measuring model fidelity fitting all research and industrial use cases [10]. Regarding model fidelity for DES, several frameworks for manufacturing and logistics applications that try to quantify the level of model fidelity have been developed. Kim et al. present a concept that compares the fidelity of DES models with a relative fidelity indicator [11]. Liu & Chen calculate the model fidelity for Discrete Event Logistics Systems (DELS) as a ratio between model feature indicators for the 4 fidelity dimensions "structural", "correlational", "temporal" and "sensorial" and use that ratio to compare the fidelity of 2 models built for an example system [12]. In this work, the 4 fidelity dimensions "workstations", "material flow", "(human) task execution" and "logic" have been used to assess the created models qualitatively, while a comparison of the throughput delivers a simple quantitative accuracy measurement.

There are several works that are investigating the creation of multi-fidelity models for DES. The basic idea is usually to derive low-fidelity models from a high-fidelity model – ideally in an automated fashion – to achieve a higher simulation speed at the expense of accuracy [8][13][14]. The research presented in this paper approaches the level-of-detail question from the other direction. The starting point is a low-detail model, which is further refined iteratively, if the simulation results, tested in a validation cycle, are not accurate enough for the simulation purpose. In contrast to simplification of model aspects from a high-fidelity model, the addition of further details to an existing model to obtain a model with higher fidelity cannot be done in a fully automated manner and therefore is mainly a manual process.

3. Research Method

DES processes usually follow the core steps "Problem & Scope Definition", "Data Collection", "Simulation Model Building", "Model Validation", conducting "Experiments" and "Outcome Analysis". Depending on how detailed the process is depicted, there are additional steps and adaptions like verification loops in conjunction with the model generation and data collection activities, additional planning aspects, documentation activities, results implementation and feedback loops in the DES method descriptions stated by a variety of authors (e.g., [15, 16, 17]).



Fig. 1. Iterative DES model development process.

The approach used for this work is illustrated in Fig. 1. In addition to the mentioned basic steps, the explicitly depicted model refinement loop emphasizes the iterative process of increasing model granularity. In this special case, the model refinement process does not lead to a more detailed version of the same model with every iteration, but rather results in a derived independent model to be able to compare the levels of detail of the created models. Each loop includes the collection of additional parametrization data and the implementation (and verification) of more detailed model elements and concepts. Subsequently, each newly derived model is validated with actual data from the real production system and compared to the predecessor models. If the fidelity of the newly created model is not sufficient to achieve the given simulation objectives, another refinement cycle is induced. After a model with adequate model fidelity is developed, the remaining steps – experimentation and analysis – are conducted to perform several optimization activities.

4. Use Case Description

The iterative modelling approach has been applied to create a DES model of the CNC machining area in a manufacturing site for vehicle cast parts of the industrial partner Nemak. The goal of the simulation process is to provide a virtual representation of the CNC area that allows to identify material flow bottlenecks, caused by insufficient resource availability, and reveal imbalances in the workload distributions for human operators. In a first step, the current state of the CNC machining area ("As-Is scenario") – as schematically depicted in Fig. 2 and described below – has been modelled with FlexSim and validated with actual data from the physical production system. In a second step, a planned "To-Be" scenario for the CNC area has been simulated and optimized to maximize the production throughput.

The CNC area consists of 4 CNC machining centers (CNC 1 - CNC 4), each able to machine one part at a time. Parts from the upstream grinding process are buffered in an intermediate storage space within charge carriers called "racks". The batch size of the racks depends on the respective part type. When the predecessor rack on the Input Rack Position (IRP) - a predefined location in front of a CNC machine for racks with unmachined parts - is empty, a new full rack with unmachined parts from the intermediate storage is transported to the respective CNC IRP ((1)). At an IRP, the parts are manually taken out of the rack and inserted into the CNC machining center (2). After the manual setup operations (3), the automatic machining process is started. When the machining is finished, the parts are removed from the CNC machine ((4))and cleaned at the associated cleaning desk ((5)) by the machine operator. Afterwards, the cleaned part is put to a rack at the Output Rack Position (ORP) in front of the CNC machine ((6)). Full racks with machined parts are transferred from the CNC ORPs to the Rack Position (RP) of the Cavity Inspection Desk (7). There, the parts are taken out of the rack again (8)

and each one is tested individually for shrinkage defects in the casting ((9)). Afterwards, the parts are put back into a rack (10). The part handling and setup activities are again done manually by a human operator, while the cavity inspection process itself runs automatically. Racks with inspected parts are forwarded to the Assembly area for the next process steps (11). In addition to the movements of loaded racks (red lines in Fig. 2), empty racks have to be maneuvered from IRPs to the empty-racks storage (12) and from there to the ORPs (red-rimmed lines, 13). All rack movements are performed manually by human operators with the aid of discontinuous conveying devices like forklifts or pallet trucks. The single piece movements (blue lines) can be done without any further technical device assistance.

Currently, 2 human operators (green dots in Fig. 2) perform all the described tasks in the CNC machining area – each one is responsible for 1 module with 2 CNC machines. The single cavity inspection desk is used by both operators in an alternating manner.

5. Model Fidelity

In total, 3 models with different levels of detail have been created and validated. The model refinement – starting at the initially created low-detail model – led to a medium-detail model and finally to a model with sufficient fidelity compared to the real production system – referred to as the high-detail model. The 3 models are described below, followed by a fidelity comparison.

Low-detail Model

The low-detail model is just a coarse representation of the material flow in the CNC machining area without the consideration of human operators. Therefore, all workstations (CNC machining centers, cleaning desks and the cavity inspection desk) are modelled as fully automated processing units with cumulated setup and processing times. The transport of the parts between the stations and buffer locations (intermediate and empty-racks storage as well as the Cavity Inspection RP) is abstracted as automated single-piece flow. The transport times for each part are added proportionally to the setup times of the receiving stations. A Bernoulli distribution function is used to reject scrap parts at the cavity inspection desk – the reject rates at the other stations are



Fig. 2. As-Is Validation scenario "CNC Machining".

negligibly small. The assignment of the correct part types to the CNC machines is realized by a simple pull-logic at the CNC machining centers. All other part flows follow a "First In, First Out" (FIFO) push strategy. Production periods and machine downtimes are configured via timetables on a weekly basis.

The simulation of the low-detail model is able to give a bestcase throughput estimation, based on the average transport and processing times of the fixed resources, without any restrictions of operator availability. While the material flow in the real system is performed with non-continuous conveying systems in defined batches, the assumption of single-piece part flows causes some inaccuracies. Obviously, the coarse low-detail model cannot be used for examining intralogistics resource bottlenecks or workload balancing.

Medium-detail Model

In contrast to the low-detail model, the part flow between the stations in the medium-detail model is more realistically modelled as batch flow. Therefore, each workstation has defined positions for incoming and outgoing racks. All single piece flows between the RPs and the CNC machines respectively cleaning/inspection desks remain unchanged. Transport times are still modeled as addition to the setup durations at the receiving RPs, but now more accurately as duration per rack movement. Contrary to the abstraction in the low-detail model, where all process steps are executed automatically, the dimension of tasks that must be performed by human workers is added to the medium-detail model. The manual tasks within the CNC machining area include the intralogistics tasks (movement of loaded and empty racks), the setup tasks for the CNC machining centers and the cavity inspection desk, and the part cleaning operations at the cleaning desks. The creation of these tasks has been implemented using the standard task templates provided by FlexSim. As defined in the use case, all these tasks are executed by 2 human operators. The sequence of execution is determined by a simple priority value. The logic for part distribution and rejection of scrap parts remains the same as in the low-detail model.

While the implemented batch transport of parts gets a lot closer to the real situation in the physical production system, and the addition of the operators allows a rough evaluation of the workload distribution of the human workers, there are still some shortcomings in the model concerning the defined simulation objectives. Because the average transport times are simply added to the setup time of the receiving stations, the transport times cannot be analysed separately. A workaround would be to add further model elements to represent the transport processes, but this solution leads to a more confusing visual representation of the model. Another problem is the task sequencing for the operators. The standard FlexSim task templates with simple sequencing priorities deliver nonsatisfying results because some tasks should be performed consecutively without interruptions, even if the interrupting task is of higher priority. Furthermore, the medium-detail model does not include changeover logic for switching between part types during a simulation run. The necessary logic has to consider a number of restrictions - e.g., when are changeovers allowed, what happens with remaining parts at the rack positions, etc. - and therefore is not easily implemented without additional custom-code.

High-detail Model

The high-detail model addresses the shortcomings of the medium-detail model with the implementation of additional functionalities for the realization of realistic changeover behavior and improved control over task sequences. Instead of using the standard task templates of FlexSim, a customized task creation and allocation system has been developed. Each station creates specific human operator task sequences, derived from customized task sequence templates, that are necessary to run the station. E.g., if the automatic processing of a part is finished at a CNC machining center, a task sequence for part removal and transport to the associated cleaning desk, is created as a single, uninterruptable sequence. The generated task sequences are added to a pool of available operator tasks, where they are assigned and subsequently executed by the predetermined operators with regard to the task sequence priority. The task priorities are still simple priority values but can be flexibly adjusted by the source station considering various environmental conditions (e.g., content of buffers, blocked machines, etc.).

Furthermore, the required changeover logic is added for the CNC machining centers and the cavity inspection desk. In case



Fig. 3. 3D representation of the high-detail model in FlexSim.

of the CNC machining centers, changeover events are defined by the corresponding machine-specific timetable but are initiated only after all relevant conditions are fulfilled (e.g., minimum time span between changeovers, all remaining parts at the IRP must be processed before starting the changeover process, etc.). For the cavity inspection desk, a changeover is initiated based on the amount of queued parts for each part type at the cavity inspection RP and a maximum changeover frequency. Again, the initiation of a changeover leads to the creation of specific task sequences that are added to the task pool.

Table 1. Qualitative comparison of the 3 models using 4 fidelity dimensions.

Dimension Aspect	Low-detail model	Medium-detail model	High-detail model
Workstations			
(Un-)Loading Positions	No	Yes	Yes
Setup Time	Yes	Yes	Yes
Process Time	Yes	Yes	Yes
Material Flow			
Transport Type	Single-piece flow	Batch Transport	Batch Transport
Manual Loading/ Unloading	No	Yes	Yes
Distinct Transport Time Parameters	No	No	Yes
Task Execution			
Human Operators	No	Yes	Yes
Task Sequence Definition	-	OOTB FlexSim Task Sequences	Customized Task Sequences
Task Allocation	-	OOTB FlexSim Mechanism	Customized Allocation System
Task Monitoring	-	Task Sequence Level	Single Operation Level
Logic			
Part Distribution Logic	Pull Logic (CNC) + FIFO Push	Pull Logic (CNC) + FIFO Push	CNC Production Program controlled
Changeover logic	No	No	Yes
Production Rejects	Yes (Bernoulli Distribution)	Yes (Bernoulli Distribution)	Yes (Bernoulli Distribution)

The task sequence creation system gives all possibilities needed to recreate realistic human operator behavior for tasks related to the production process. Since the custom task sequences are easier to access than the Out-Of-The-Box (OOTB) task system provided by FlexSim, detailed workload analyses for operators are much easier and possible even on single operation level. The implemented changeover mechanism allows to simulate production program changes by simply editing a CNC machine's timetable – all necessary changeover activities are handled automatically by the model logic. Since most of the logic for changeovers and task initiation is implemented in a station itself to form a modular unit, and in conjunction with the task sequence creation system, the high-detail model provides easy extensibility with additional workstations of the same type – additional stations just create more task sequences enlarging the task pool for any number of operators.

While the low- and medium-detail models have been built only with FlexSim Standard 3D modelling elements, the highdetail model includes process flow control constructs and custom-code functions for implementing the additional logic. Fig. 3 shows a screenshot of the 3D representation of the highdetail model during simulation in FlexSim. Some additional abbreviations for the cavity inspection desk (CID) and the cleaning desks (CD) are used in the simulation environment. Furthermore, the figure shows a "PartCreation" section for instantiating flow items in the model as well as additional buffer queues ("CDX Buffer") for the cleaning desks and a scrap part location at the CID area ("CID_Scrap"). All the other depicted model elements correspond with the schematic illustration in Fig. 2. Table 1 summarizes the differences of the created models using the 4 defined fidelity dimensions and their subordinated aspects.

6. Results and Discussion

For a quantitative evaluation, a maximum deviation of $\pm 15\%$ from the actual average throughput of the physical production system was predefined as the decisive indicator, if the throughput of a model is accurate enough for further experimentation. The throughput of each model was measured for a 2-day (equals 6 shifts) simulation time during the model validation process. Subsequently, the average outcomes of 20 simulation runs per model were compared to the average throughput of the physical CNC area production subsystem, measured over a 2-month period. The simulation duration and cycles could be kept low because at the time of those validation cycles no machine breakdown logic has been implemented, and therefore the variance of the outcomes was marginal. To guarantee comparability to the simulation data, production start periods and production intervals that included breakdown events have been excluded from the validation data as well. The validation runs were performed with 2 simultaneously machined part types (PT 1 on CNC 1 & 4, PT 2 on CNC 2 & 3). The results are shown in Table 2.

Table 2. Average Deviation of the model throughputs from the average production volume (normalized, 20 simulation runs/model).

Part Type	Low-detail model	Medium- detail model	High-detail model	Actual Average Production
PT 1	+26.71%	+15.30%	+12.61%	100%
PT 2	+26.38%	+16.47%	+11.51%	100%

Because of the various idealizations, all 3 models deliver higher throughputs than the real production system. The lowdetail model without any task executer restrictions delivers around +26.5% more throughput than the real production system, while the medium-detail model with implemented human task executers is with +15.30% and +16.47% much closer to reality and almost inside the tolerated deviation range. Because of the improved and more realistic task sequencing provided by the customized task system, the accuracy of the high-detail model improves to an average of +12.61% and +11.51% over the conducted simulation runs and therefore meets the accuracy requirement. One big factor for the remaining inaccuracy even in the high-detail model are short-duration downtimes at the CNC machining centers, caused by a variety of unforeseeable events like delayed start of the CNC program due to safety alerts (e.g., doors not closed), necessary manual readjustments in the setup process, and others. This kind of interruptions are difficult to measure during daily business and therefore currently not captured in the models.

After all qualitative and quantitative requirements have been fulfilled by the high-detail model, no further model refinement cycles were needed. Based on the high-detail model, the simulation and optimization of a To-Be scenario with 6 CNC machining centers, 4 operators and a second cavity inspection desk, including a rearranged area layout, brought an increased throughput of +29.6% compared to the conventionally, experience-based planning. The improvement was mainly achieved by

- re-allocation and -prioritization of the human operator tasks, so the workload distribution between all operators is quite even and on a high level,
- detection of the cavity inspection as bottleneck station, and therefore shifting dedicated operator resources to optimize the cycle times of the cavity inspection desks, and
- optimized changeover frequencies of the CNC machining centers with consideration of the material flow requirements of the downstream processes.

7. Conclusion and Outlook

In industrial optimization projects, usually it is not feasible to create multiple models with different levels of detail, because it is too time-consuming and/or too expensive. While the presented comparison of models with varying levels of detail and fidelity compared to the physical system can be used as a rough guideline for future modelling activities with comparable objectives and boundary conditions, more simulation results gathered from similar use cases are necessary to ensure the representativeness of the stated results.

Another interesting extension of the research would be further refinement loops to achieve even higher model fidelity and accuracy, e.g. the consideration of transport devices, if they are bottleneck resources, or additional operator tasks, that may occur in the day-to-day business at the shop floor, and so forth. Such further detailing only makes sense, if there is enough input data available to parametrize the model accordingly, and the implemented details bring added value to the analyses for the defined purpose of the simulation model.

The use case described in this paper is part of a bigger ongoing research project with the objectives to generate coherent virtual representations of production and logistics systems to establish Digital Twins (DTs) with self-optimization capabilities. Currently, the use case described in this paper is extended to the upstream process steps to cover the whole production site. The generated production system model will be used as foundation for the virtual counterpart to the physical production system in the upcoming DT implementation. Further details will be published in a follow-up paper.

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