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Editorial

Dear Readers, This third issue of SNE Vol. 32, 2022 , sustains the traditions of SNE special issues for EUROSIM conferences – with this SNE Special Issue ASIM SPL 2021 – Simulation in Production and Logistics. ASIM, the German Simulation Society, is running two bi-annual conference series, the 'ASIM Symposium Simulation Technique', and the 'ASIM Dedicated Conference on Simulation in Production and Logistics'. The Special Issue Editorial Board has selected seven outstanding contributions from ASIM SPL 2021 for publication in SNE, compiling a successful special issue as with SNE 30(4) – SNE Special Issue ASIM SPL 2019 Conference, and SNE 27(2) – SNE Special Issue ASIM SPL 'Impact of Energetic Factors' – and hoping for the next SNE Special Issue ASIM SPL 2023 with contributions from the next conference in this series (September 2023, Ilmenau).
This issue also continues another SNE tradition: as with SNE Vol. 30, 28, 25, 23, and Vol. 21, Vlatco Čerić, Past President of the Croatian Simulation Society, provides his artwork as cover pictures for SNE Vol. 32, 2022. 'Algorithms, mathematics and art are interrelated in an art form called algorithmic art. Algorithmic art is visual art generated by algorithms that completely describe creation of images. This kind of art is strongly related with contemporary computer technology, and especially computer programming, as well as with mathematics used in algorithms for image generation' – as Čerić defines (vceric.net). For this issue, we have chosen the Picture no.4 of the series AMULETS. Vlatko Ceric's graphic art is based on algorithms, which step by step generate the graphic result – an analogon to the algorithms used in discrete simulation – the basis for the work presented in this special issue.

We thank the special issue editors for their excellent editorial work (for details, see the special issue editorial). I would like to thank all authors for their contributions to SNE 32(3) showing the development of (mainly) discrete simulation and application in production and logistics. And last but not least thanks to the SNE Editorial Office for layout, typesetting, preparations for printing, electronic publishing, and much more.

Felix Breitenecker, SNE Editor-in-Chief, eic@sne-journal.org; felix.breitenecker@tuwien.ac.at

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Editorial SNE 32(3) – SNE Special Issue *ASIM SPL 2021*

SNE 32(3), the **SNE Special Issue ASIM SPL 2021**, comprises a selection of outstanding contributions of the 19th ASIM Dedicated Conference **Simulation in Production and Logistics** (ASIM SPL 2021), which took place in September 2021 as an online-Conference, organized by FAU Erlangen-Nürnberg and TH Ingolstadt.

Every two years, this conference – as Europe's largest conference on simulation in production and logistics – is organized by the **ASIM** Section *Simulation in Production and Logistics* (SPL) and presents trends, research results, developments, and significant industrial applications. The conference in the year 2021 focuses compelling topics like energy and sustainability, data science and artificial intelligence, applications in factory control and logistics as well as verification and validation.

The consideration of energy aspects in the simulation of manufacturing systems stands in the context of operational efforts for carbon-neutral production and sustainability. *Schreiber et al.* introduce a simulation-based optimization approach for eco-efficient orchestration of a supply chain with an objective system consisting of three sub-objectives: cost, energy efficiency and service level. By coupling the simulation model with a Non-dominated Sorting Genetic Algorithm, new configurations of decision variables are generated after a series of simulation runs. *Ventura Silva et al.* describe a simulation-based methodology for evaluating indirect and direct energy demand and costs associated with production scrap. Based on a combined discrete-event and agent-based simulation, scenarios with different rates are simulated. The results show that the impacts associated with production scrap are different for each process and are influenced by various factors.

Rippel et al. design a possible optimization of the supply to install offshore wind farms. The idea is to combine mathematical optimizations with a cascading discrete-event simulation to select online from a previously optimized cycle during project execution. This combination brings together the best of both methods by optimizing each route separately through high flexibility while reducing the search space.

In the context of Artificial Intelligence (AI), the method of knowledge discovery uses simulation data or simulation models as data generators (data farming). *Genath et al.* present an integrated solution that enables the creation of experimental plans, implements a method for distributing the required experimental runs, and empowers the user with tools for analyzing and visualizing the result data.

Studies on logistics concepts and the design and control of handling technology and conveyor systems are a traditional application field of simulation, which still contains many interesting innovations. *Voss et al.* present a combination of analytical approach and simulation to solve the problem of combined container stowage and ship routing. The newly developed mathematical model is used to calculate the optimal stowage plan while optimizing the terminal rotation. The optimal solution is tested for robustness using simulations. There are various approaches to parcel delivery. *Davidsson et al.* have evaluated a novel transportation solution in which electric vehicles dynamically deploy smart freight boxes from which customers can pick up their delivery at any time of day. This gives customers more flexible access to their parcels and allows the service provider to deliver parcels more efficiently.

Some contributions of the conference have addressed the topics of verification and validation. *Overbeck et al.* show a potential way to extend the useful and usable time slot for simulation models. This is to introduce a method for automatically comparing simulation models with actual production systems and then allowing the model to self-adapt to reality to maintain and even improve its accuracy over time. An improved simulation model can be defined as a digital twin of the production system.

The editors express their gratitude to all authors for their great effort and cooperation. For this **SNE** issue, they have revised and in some cases expanded their original conference contributions, thus providing interesting insights into current considerations and the spectrum of scientific discussion. Furthermore, the editors would like to thank the reviewers for their substantial and precious support towards a special issue of high scientific quality. Last but not least the editors thank the **SNE** Editorial Office for the support in compiling this special issue and for the opportunity to make the issue an 'early' **SNE** September issue, ready for the **ASIM 2022** Conference in Vienna, July 2022.

The editors hope that you will enjoy this **SNE** issue, that it contains valuable suggestions and that it will encourage you to participate actively in the next **ASIM SPL** conference, which will take place in Ilmenau, Sept. 13 - 15, 2023.
www.asim-fachtagung-spl.de

Sincerely, the SNE 32(3) Special Issue Editors

Jörg Franke, FAU Erlangen-Nürnberg,
Eva Russwurm, FAU Erlangen-Nürnberg;
Peter Schuderer, TH Ingolstadt,
Sigrid Wenzel, Universität Kassel
in the name of the ASIM Dedicated Conference

Development of an Integrated Solution for Data Farming and Knowledge Discovery in Simulation Data

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Abstract. Simulation is an established methodology for planning and evaluating manufacturing and logistics systems. In contrast to classical simulation studies, the method of knowledge discovery in simulation data uses a simulation model as a data generator (data farming). Subsequently, hidden, previously unknown and potentially useful cause-effect relationships can be uncovered on the generated data using data mining and visual analytics methods. So far, however, there was a lack of integrated, easy-to-use software solutions for the application of the data farming in operational practice. This paper presents such an integrated solution, which allows generating experiment designs, implements a method to distribute the necessary experiment runs, and provides the user with tools to analyze and visualize the result data.

Introduction

Simulation is an established tool for planning and controlling complex production and logistics systems and has proven to be an important key component, among other things, in solving challenges in the context of Industry 4.0 [8]. Traditional simulation studies are usually designed to cover a previously defined project scope or to achieve a concrete project goal through manual experimentation. This includes, for example, the optimisation of a production layout [9].

With increasing computing power and the general availability of Big Data infrastructures and cloud-based solutions, as well as considerable progress in the field of data mining, another possible application for simulation models arises: conducting a very wide range of experiments to uncover hidden, previously unknown and potentially useful cause-effect relationships. Particularly in complex systems, there may be relationships, problems or even solutions that go beyond the defined goal of a traditional simulation project and can therefore contribute to decision support. The basis for this approach is the methodology of data farming [5].

Based on data farming, Feldkamp et al. [4] developed a method named Knowledge Discovery in Simulation Data, which supplements data farming with methods from data mining and visual analytics, specifically suited for the analysis of production and logistic systems. Initial case studies have proven its potential [1, 2].

However, a broad transfer into operational practice was so far held back due to the lack of an integrated software solution that also enables non-simulation or data farming experts to conduct knowledge discovery in simulation projects.

This paper presents such an integrated solution, which initially extends the existing software solution SimAssist (cf. [13]) as a prototype. The development was carried out within the framework of the German Federal Ministry of Education and Research (FMER) project "Development of an integrated solution for data farming and knowledge discovery in simulation data (DaWiS)". The sub-aspects to be considered here are procedures of intelligent experiment design, methods for the (cloud-based) distribution of experiments as well as the selection and adaptation of suitable data mining and visual analytics methods, so that data farming or the method of knowledge discovery in simulation models according to Feldkamp [1] can be effectively applied with little training effort.

In this paper, the methods and the implemented software solution are explained using an example from the automotive industry. The actual simulation is carried out in the simulation software Siemens Plant Simulation.

The remainder of the paper is structured as follows. First, the state of research and the necessary theoretical foundations of data farming and the method for knowledge discovery in simulation data (KDS) are presented briefly. Then, in Section 2 the main part of the paper, the integrated method is presented step by step, and illustrated by a workflow example. At selected points, particular attention is paid to the technical implementation. The article ends with a conclusion and an outlook on possible extensions of the integrated solution.

1 State of the Art

In data farming, a previously validated simulation model is used as a data generator to cover the largest possible spectrum of model or system behaviour (response surface) with the help of intelligent experiment design and high-performance computing [5, 10]. The "farming" metaphor expresses that the goal is to maximise the data yield of the simulation model, analogous to a farmer who cultivates his land as efficiently as possible to maximise his crop yield [11].

The research and development of improved procedures for the design of simulation experiment plans is one of the crucial prerequisites. These allow possible combinations of factor values to be comprehensively represented and at the same time guarantee a reasonable number of experiment runs to generate data [7, 12]. Especially in the context of the simulation of production and logistics systems, the selection of one of the design methods or even the selection of a suitable combination of different design methods is of great importance. To carry out the experiments, the data farming literature often refers to appropriate high-performance computing [5].

Interesting relationships can then be uncovered in the generated data with the help of various data mining or visual analytics methods [6]. This way, previously unknown relationships, problems or even solutions can possibly be identified.

Feldkamp [1] presents a selection of possible data mining methods, e.g., clustering, and the appriopate workflow for applying those methods contiguously. It is recommended that the actual analysis of the generated simulation result data and the relationships between factors and result data (key figures) is ideally supported with interactive, visual analysis. Visualisation is generally a crucial tool when an interpretation of data is required. A consistent dovetailing, as is generally recommended in the research discipline of visual analytics, between interactive visualisation, e.g., by means of interactively adaptable animations, time series diagrams, graphs, and data analysis by means of data mining methods, enables the user to incorporate the human ability to draw conclusions in the best possible way [3, 6].

In summary, the state of the art in science and technology in this context shows that the basic individual methods (data farming, intelligent experiment design, data mining and visual analytics) have reached a sufficient maturity level. Prototypical applications in the context of simulating production and logistics systems demonstrating the potential of this approach have also been published. However, it must be stated that there is yet no holistic solution for transferring the methods as a whole or at least in significant parts into a framework that can be operated by non-experts, and which also focuses on the area of simulation in production and logistics. Furthermore, there is a lack of methods for (partial) automation of the processes and for supporting non-experts in general.

2 Integrated Solution for Data Farming and Knowledge Discovery in Simulation Data

As already mentioned in the introduction, the aim of the FMER research project DaWiS is to develop a software solution, supplemented by best practice procedures, which also allows non-experts to acquire knowledge based on data farming using data mining and visual analytics methods.

For this purpose, the proven modular software SimAssist (cf. [13]) by Simplan AG, which already provides extensive assistance functions for the administration, analysis, visualisation, and documentation of result data of classic simulation projects, has been expanded.

The extensions are combined in a new module of the software call “4farm”. Corresponding components were designed and prototypically implemented for the already mentioned sub-aspects, the intelligent experiment design, the distribution of experiments as well as for the data mining and visual analytics. The basic architecture of the module can be seen in Figure 1.

It is worth mentioning that in addition to research on the methodology, substantial effort was put into the design of the user interactions during the conception and development, so that all necessary sub-aspects (from experiment design to the distribution of experiment runs to the analysis and visualisation of data) are available via an integrated interface without changing the software.

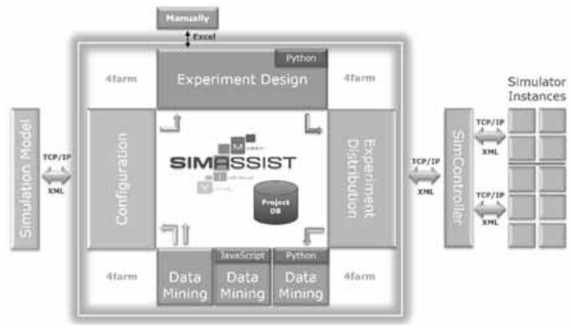

Figure 1: General architecture of the software solution (SimAssist – 4farm module) for data farming and knowledge discovery in simulation data.

Furthermore, as many technical details as possible are hidden from the end user, especially regarding the experiment design, the data mining and visual analytics methods, necessary settings are anticipated based on best practices. If this is not possible, the necessary settings are transferred to an intuitively understandable technical application level. This is done by asking for the necessary parameters when using the methods. In each case, the user is offered lists with selection options.
The corresponding notes on the use as well as the advantages and disadvantages of the individual variants are stored in the software in the form of information texts or decision trees or in a similar way. The user can thus focus completely on the simulation model and objective of the simulation study.

Due to the rapid development of research in the field of data mining and visual analytics, but also due to the large number of possibilities regarding experiment design, another requirement placed on the software is that new methods, including visualisations, can easily be added in the future via a standardised mechanism.

2.1 Workflow Example – Supplying a Car Production Line with Batteries

In the context of this paper, selected methods as well as the implemented software solution - especially the excerpts of the user interfaces - are presented based on an example scenario. Among other use cases, this example was used in the DaWiS project starting with the requirements analysis until the final demonstration of the methods and the software.

The workflow example includes a typical logistical problem in which the supply of a running car production with two different types of batteries as well as the disposal of the stackable empty load carriers is considered. The delivery of the batteries in load carriers and the collection of the empty load carriers is done by truck at an unloading dock. The actual handling of the batteries is done by forklift trucks (Figure 2).

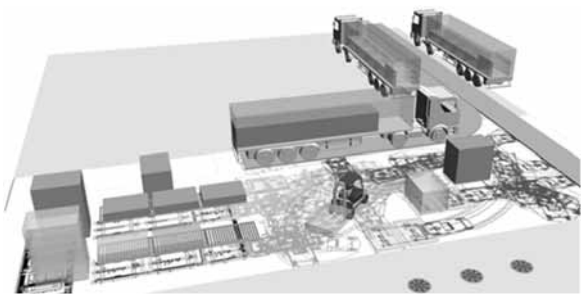

Figure 2: Screenshot of the model of a loading/unloading of batteries to supply a running production.

The variable input parameters (factors) of the model include the ratio of battery types A and B in the total production programme of the vehicle assembly (which itself is not part of the simulation model under consideration). Further factors of the simulation model are the total production volume, the cycles in which trucks deliver new batteries and the size of the buffers for full loads. In addition, three different scenarios are defined, each of which differs in the forklift variants used (5t or 8t forklifts) and the number of forklifts (1-2 forklifts). To analyse the results, 31 result parameters are stored, including the forklift utilisation or the downtimes of the connected assembly due to missing batteries.

The model of the production and logistics system was created using the Siemens Plant Simulation software. Here, modules were developed which enable the setting of the factor values (variables to manipulate) and the readout of the pre-definable result data (XML format).

With the help of these modules, models can be enriched with meta-information about the factors and result parameters as well as their data types and, if applicable, existing value ranges. This information can be evaluated by the integrated solution and presented to the user and used as a basis for the concrete experiment design.

2.2 Experiment Design

As described earlier, generating suitable experiment designs is the first major challenge in the process of data farming and thus also in the method for knowledge discovery in simulation data that builds on it. Currently, five different experiment design methods have been selected and implemented: the full factorial design, the 2^k-design, the central composite design, and the Latin Hypercube Sampling (LHS) as well as a design in which an LHS can be crossed with another factor or design.

It should be noted that experiment design methods sometimes require method-specific parameters in addition to the parameters describing the factors, i.e., the names of the factors, the data type and value range of the factor. For example, in case of the LHS, the number of experiments must be specified. All design methods are implemented as Python scripts. The scripts use a uniform library for XML-based data import and export and can contain corresponding meta-information as comments at the beginning.

The information about the factors can be set manually or – as indicated in the previous section – read out from the simulation model. The design method-specific parameters are queried from the user in SimAssist. Which parameters are queried and how the interface is designed in the SimAssist 4farm module is defined in the meta information of the respective script.

Adding further experiment design methods is possible at any time without restarting the software. To do this, the methods only must be made known as Python scripts annotated with the addressed meta information by copying them into a defined directory (so-called hot deployment). The corresponding selection option and the interfaces are generated ad hoc and can be used immediately.

When selecting the experiment design methods, the user is supported on the one hand by textual help for the individual methods. On the other hand, assistance is available in the form of a decision tree (Figure 3), in which a design method is suggested by answering simple questions.

In the example scenario mentioned here, a crossed LHS design with 15,000 experiments (5000 LHS * 3 scenarios) was used due to the different scenarios (green/dashed path in Figure 3).

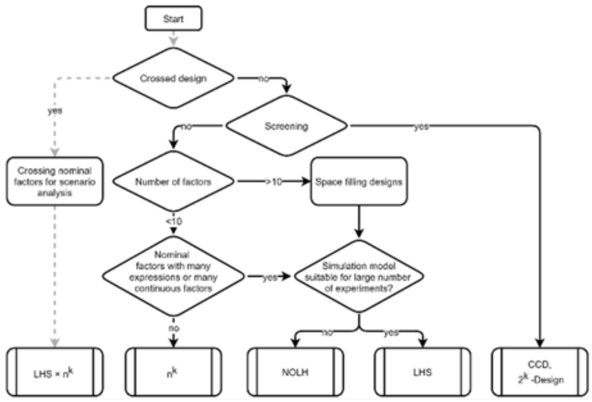

Figure 3: Flowchart for selecting the appropriate experiment design methods [1].

2.3 Experiment Distribution

Due to the large number of simulation runs, it is usually not practical to carry out the experiments on a single computing instance (single computer or single processor core on a single computer). Instead, it is desirable to distribute individual experiments across different computing instances. The technology used in the DaWiS project is based on a software component from a preliminary project of Simplan AG, the so-called SimController. This was adapted in such a way that it is now possible to distribute experiments, i.e., models and the concrete factor values in the form of XML data via a central instance to self-registering client instances using TCP/IP. The individual instances continuously report their status.

After running an experiment, the defined characteristic values (and used factor values) are reported back to the central instance and stored in SimAssist in the form of a SQLite database. This data can then be used and analysed very easily.

2.4 Analysis of the Result Data – Data Mining and Visual Analytics

Analogous to the experiment design methods, the number of possible data mining methods and visualisation methods is very large. In the method for knowledge discovery in simulation data, Feldkamp [1] analyses different groups of methods and provides an assessment them with regards to their benefit for knowledge discovery.

Based on this research, methods of descriptive statistics, correlation analysis, clustering (k-means and gaussian mixture) as well as regression analysis and the formation of classification trees were classified as most valuable for practical application and implemented in the prototype. In addition, there are suitable visualisations such as heat maps for correlation analysis or parallel coordinate and scatter diagrams for the evaluation of clustered data. The technical implementation here is analogous to the implementation of the experiment design methods, i.e., each of the methods is implemented as an annotated Python script and the data exchange with the script is again carried out via XML format. Here, too, it is thus easy to implement further data mining methods and visualisations, which are immediately available to the user via generic dialogues from the 4farm module for knowledge discovery.

The data analyses within the workflow example have not yet been completed. However, initial findings are emerging. For example, it turns out that assuming the current demand for batteries, every scenario leads to a secure supply of production. However, even with a moderately increasing proportion of battery electric vehicles, scenarios with two forklifts, at least one of which is an 8t forklift, work better, especially if one battery type is in demand significantly more often.

3 Conclusion

The paper presented an integrated software solution developed for knowledge discovery in simulation data. For this purpose, the need for and the requirements of such a solution were derived and the essential sub-aspects of the method and its user-friendly prototypical implementation were examined in more detail. Further development steps include the implementation of additional experiment design and data mining methods as well as additional visualisations. Moreover, further tests in real-world use cases are necessary, especially to validate the implemented interfaces and file formats. Finally, research on further (partial) automation of the data mining methods, e.g., by means of meta-learning to determine suitable hyperparameters, or the use of methods for robustness analysis, is conceivable.

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Federal Ministry
of Education
and Research

Simulation-Based Optimization for the Design of Eco-efficient Supply Chains

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Abstract. The efficient design of supply chains incorporating ecological objectives is a strategic task that is increasingly attracting the attention of companies. This paper introduces a simulation-based optimization approach to eco-efficiently orchestrate a supply chain with a target system consisting of three sub-targets: Costs, energy-efficiency and service level. Regarding a use case from the steel processing industry, an event-discrete simulation model of the corresponding supply chain was configurated. By interfacing the simulation model with a Nondominated Sorting Genetic Algorithm new configurations of decision variables are generated after a set of simulation runs. The evaluation of the experiments and the resulting pareto sets led to the identification of promising eco-efficient configurations and the derivation of corresponding decision variable assignments for the use case which consist of material allocation, reorder point and replenishment level.

Introduction

Rising global demand for energy as well as raw materials pose a major challenge for the manufacturing industry. Due to the scarcity of fossil fuels, sustainability in the industrial sector is becoming increasingly important. Nevertheless, according to the German Federal Ministry of Economic Affairs and Energy, the energy consumption in this sector increases significantly [1]. Efforts at the interface between research and application are necessary to enable companies to counter these contradictory developments.

In the context of supply chain management, ecological goals are increasingly being integrated into corporate decisions. Eco-efficient approaches represent a decisive strategy for the design of sustainable supply chains [2]. In this context, ecological goals have to be integrated into the target system of the value network, and, at the same time, economic efficiency has to be maintained or increased. However, supply chains are highly dynamic and complex systems with multiple dynamic interdependencies. Accordingly, efficient methodological tools are needed that can map and evaluate supply chain interdependencies and achieve improvement in supply chain parameter configurations. The event-discrete material flow simulation is an established tool to digitally replicate and evaluate different control logics and parameter settings of individual entities. Linear optimization models as well as metaheuristics are, among other, suitable for the optimization of value chains [3]. Due to the complexity described above and the associated large solution space of possible design options for a value chain, it is difficult to generate exact solutions for a given modelled problem. Furthermore, a purely mathematical formulation of the model is often challenging due to the large number of objects, dependencies and stochastic uncertainties associated with these problems.

Combining both metaheuristics and simulation utilizes the advantages of both tools [4]. According to the VDI, this so-called simulation-based optimization can be implemented in four different ways [5]. In this paper, an integrative coupling shall be implemented to guide in the decision-making process. The (multi-criteria) simulation results serve as an objective function for a genetic algorithm. According to the VDI, this corresponds to a “Category D” approach. The three-dimensional target value system consists of costs, energy consumption and service level.

A genetic algorithm is used to create new configurations of supply chain input parameters for the simulation model after a series of simulation runs. For this paper, the genetic algorithms used are the „Nondominated Sorting Genetic Algorithms (NSGA)" NSGA-II and NSGA-III.

Through an implemented interface, newly generated configurations are automated and iteratively tested in subsequent simulation runs. Based on the state of the art and to differentiate the approach from previous papers, a specific demonstrative application from the steel processing industry is presented. Based on a sensitivity analysis to narrow the search space to initially preclude deficit solutions, the developed methodology is experimentally tested and the results are evaluated.

1 Simulation-based Optimization for Supply Chains

The use of simulation-based optimization for the orchestration and configuration of supply chains is a broad field of research. This chapter is dedicated to the consideration of current solution approaches of simulation-based optimization, especially for the strategic and tactical design of processes in value networks.

A methodology for a simulation-based optimization with an NSGA-II algorithm of the supply chain of a steel trading company was presented by Rabe et al. in which user-defined action plans, which address inventory parameters and material reallocations, can be designed [6]. The target system includes both cost and service-level, but does not integrate environmental metrics. Furthermore, besides the NSGA-II algorithm a Deep Reinforcement Learning (DRL) approach is used instead of NSGA-III.

Another "Category D" approach by Benyoucef and Xie focusses on a use case in the automotive industry, in which a two-dimensional target system consisting of cost and service level was also considered. Here, the solution space was restricted by limiting configurable parameters such as the order quantity and the reorder point with upper and lower limits in the potential occupancy [7].

Other approaches exist that incorporate emission values in two-dimensional target systems [8] or elaborations that implement other metaheuristics, such as a Particle Swarm Optimization (PSO) [9].

An up-to-date and detailed review of the current research of simulation-based optimization for value networks can be found in the paper by Tordecilla et al. [10].

From this, it is particularly clear that the target size system of the use case considered in this paper, with its three dimensions of cost, service level and energy efficiency, represents a differentiation from previous works.

2 Use Case Description

The use case for this paper is a supply chain of a steel processing service provider with several distribution and processing centers. The service provider offers services in which standard sizes of steel products are transformed to customer-specific dimensions and shapes by various processing machines. For this purpose, a pool of processing machines is available at various locations. The supply chain consists of five distribution centers and 25 customer regions. A simplified form is shown in Figure **1**.

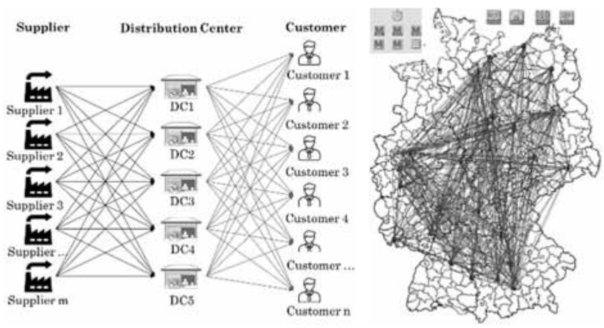

Figure 1: Representation of the supply chain of the service provider.

2.1 Procurement, Production and Distribution in the Use Case

In the following the basic processes of procurement, production, and distribution within the supply chain of the service provider are shown, which are integrated into the mechanisms of the simulation model.

Incoming customer orders are first divided into order lines. Based on the stock levels in the distribution centers, these are checked to determine whether the order can be accepted. Due to individual material allocations, scenarios may exist in which not all standard sizes are stocked in all distribution centers. In the case that several distribution centers store the material of an order in sufficient quantity, a distance-based allocation is made so that the distribution center accepts the order that is geographically nearest to the customer region of the ordering customer. If there is not enough material in the supply chain, the order is rejected. This must be considered accordingly in the service level.

The monitoring of the distribution centers' stock levels is thus an integral part. The service provider operates with an order point stock level strategy, called (s, S)-order policy [11]. If, within the scope of this ordering policy, a stock level falls below a defined reorder level s, the service provider triggers a purchase order with the supplier, which replenishes new standard sizes to a maximum target stock level S, defined individually for each product.

The production process represents the customized processing of existing standard sizes or residual sizes from previous machining processes. A distinction is made between the sawing of profiles and beams and the cutting of sheets (seen in Figure **2**). The times of the respective sawing and cutting processes depend on the cross-section of the material to be cut as well as the sawing or cutting speed of the machine. In addition, the feeding rates as well as loading and unloading times of the machines are included in the total processing time. Each distribution center has an individual pool of machines with different attributes regarding processing speed, capabilities for processing specific materials and energy consumption.

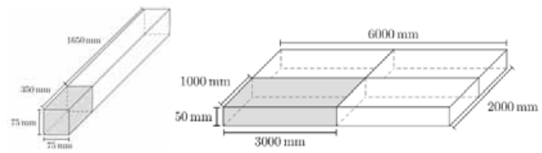

Figure 2: Example processing operations of the service provider.

On the distribution side, order picking and loading is based on the weight and volume of the finished products and the maximum quantity and volume capacity of the transport trucks. They depend on the customer's desired deadline, as well as route minimization. In addition to the company's own trucks, there is also the option of calling a shipping agent.

2.2 Target System of the Use Case

An important aspect is the ability to quantify the individual components of the target system consisting of cost, energy consumption and service level.

Costs. As the first objective function of the target system, the total costs are calculated, which consist of the sum of the transport costs, the order costs, the inventory costs, and the backorder costs.

The objective function thus results in:

$$ZF_1 = C_t + C_o + C_{inv} + C_{bo} \quad (1)$$

where:

- C_t : transport costs [in €]
- C_o : order costs [in €]
- C_{inv} : inventory costs [in €]
- C_{bo} : backorder costs [in €]

The cost positions transport costs and order costs are also divided into a fixed and a variable portion. Fixed transport costs are incurred once for a transport. A distinction is made between the fixed costs for a forwarding agent and the fixed costs for transporting a company truck. This applies analogously to the variable transport costs. A different cost rate is used for the shipping agent compared to the company's own trucks. Variable costs are calculated on an hourly basis depending on the duration of a tour. This stems from the total distance of the tour divided by the average speed of a truck.

Ordering costs are always incurred if a stock level falls below a predefined reorder level and an order for the respective material is then placed with the supplier.

The variable order costs of an order result from the multiplication of the order quantity with a variable order cost rate. In addition, a fixed cost rate is added for each purchase order. Inventory costs are always variable costs.

For each storage unit, the individual storage period is the basis for calculating the inventory costs. This is multiplied by the daily inventory cost rate to determine the inventory costs. Finally, the shortage costs result from multiplying the number of the order lines, which couldn't be fulfilled, by the corresponding backorder cost rate. The total costs are to be minimized in this optimization problem.

Energy Consumption. The second objective is to minimize the energy consumption of the sawing and cutting machines (measured in megajoules [MJ]). The processing times, feed rates and technical conditions of the individual machines play an essential role in the calculation. To determine the energetic power consumption of a saw, it is assumed that energy is only consumed by a saw when a workpiece is in its feed or the saw is busy machining a workpiece. For the machines, the drive powers of these two actuators are in the unit kilowatt [kW].

Based on the process times for the feed as well as the machining of an order position and the drive powers of both actuators of a specific saw, it is possible to determine how many kilowatts are consumed for the machining of the respective order.

By multiplying the respective machining times, the energy consumption can thus be determined in kilowatt hours. For the machining of a product of an order line, the following formulation is used to calculate the energy consumption:

$$P_{OL} = \frac{t_{TotFor}}{3600\,{}^{s}/_{h}} \times P_{For} + \frac{t_{TotSaw}}{3600\,{}^{s}/_{h}} \times P_{Saw} \quad (2)$$

where:

- P_{OL} : power consumption of a saw from the processing of an order line [in kWh]
- t_{TotSaw} : total sawing time of an order line [in s]
- t_{TotFor} : time for the feed of all workpieces of an order line through the sawing machine [in s]
- P_{For} : drive power of the actuator for controlling the feed of the workpieces [in kW]
- P_{Saw} : drive power of the actuator for the sawing process [in kW]

By multiplying with the factor 3.6 MJ/kWh, the kilowatt hour is converted into megajoules. Since an order is divided into individual order lines and these may be processed in different distribution centers, the sum of the power consumed by positions ($i = 1, \dots m$) must be used to determine the energy consumption for an order:

$$ZF_2 = \sum_{i=1}^{m} P_{OL_i} \times 3{,}6\, MJ/kWh \quad (3)$$

Service-Level. The third dimension of the target system is the degree of service-level and the delivery readiness achieved, respectively. This is a logistical indicator that provides information on the average delivery capability of a company within a given period. In principle, there are various calculation bases for calculating the degree of readiness to deliver. In the context of the use case, the so-called β-Service-Level is sued to quantify the delivery capability. From a practical stand point, this is used as the preferred performance criterion because the amount of a shortfall is included in the calculation basis [11].

Mathematically, this is defined as follows:

$$\beta = \frac{Fulfilled\ orders\ per\ time\ period}{Period\ demand} \quad (4)$$

The calculation of the β-Service-Level implies that the best performance is achieved with a value of $\beta = 1$, since in this case any period demand could be met. In terms of optimization, the value is to be maximized accordingly. Since the other two objective functions are to be minimized and a combination of minimization and maximization is more difficult to realize with multicriteria metaheuristics, the counter probability of the degree of readiness to deliver is minimized. Mathematically, the third objective function thus results in:

$$ZF_3 = 1 - \beta \quad (5)$$

3 Decision Variables and Solution Space

As described in the previous chapter, the company's target system consists of the three components cost, energy consumption and service level. To optimize this multicriteria target system, variations of logistic parameters are investigated, which represent the decision variables of the system. The parameters to be studied are the reorder point s per product p in distribution center j, the target stock S per product p in distribution center j, and the allocation of products to specific distribution centers in the form of material reallocation strategies:

- S_j^p : target stock for product p in distribution center j in days $\in \mathbb{Z}^+$
- s_j^p : reorder point for product p in distribution center j in days $\in \mathbb{Z}^+$
- l_j^p : binary material allocation for product p in distribution center $j \in [0{,}1]$

To address the initially shown problem of the large solution space, a sensitivity analysis of the supply chain to different inventory parameters was performed before coupling the simulation with the metaheuristic in order to limit the search space to promising possible combinations of reorder points and target inventories. This analysis technique is used to determine the sensitivity of the target functions as a function of the input parameters [12].

For this purpose, the average demand quantities per product were converted into inventory ranges and all potential combination possibilities up to a defined upper limit were evaluated iteratively in automatically triggered simulation runs. For this, all combination possibilities were equally distributed among the distribution centers. Figure **3** shows the total costs of the network depending on the parameter settings.

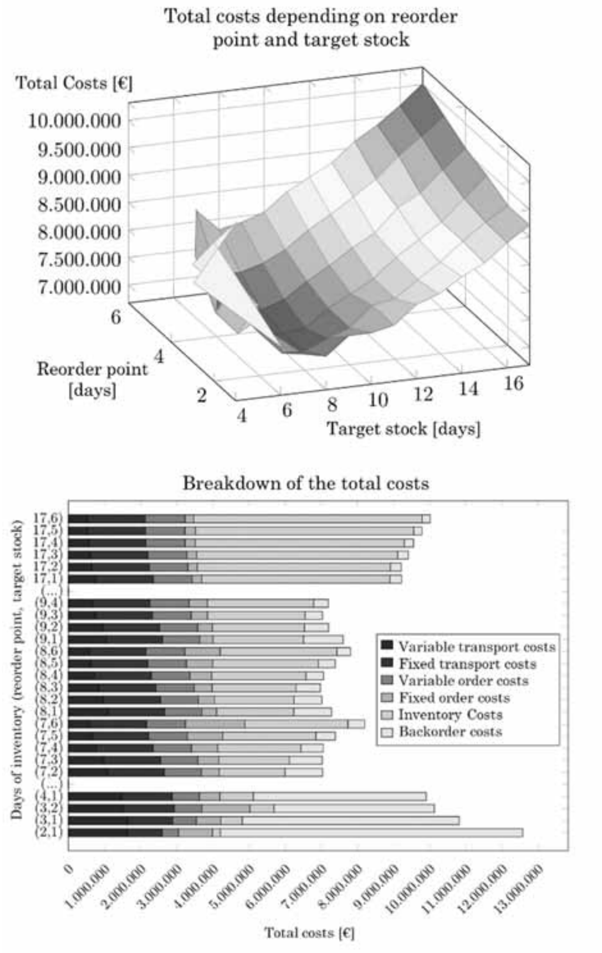

Figure 3: Sensitivity analysis of the total cost of the network as a function of the inventory parameters.

The cost function takes a convex form, at least for the parameters tested. This is a good implication that the local minimum found is also a global minimum.

To achieve a better interpretation of the results regarding the costs achieved, the subsumed total costs are also broken down in Figure **3**. This shows that the most significant differences occur in the shortage costs and the inventory costs.

This finding can be attributed to a classic trade-off effect in inventory management, in which high inventories lead to high capital commitment costs, whereas low inventories lead to shortage costs. With low reorder and target stocks, the risk of incurring a high sum of shortage costs is therefore higher. By contrast, minimizing this risk leads to high inventory costs.

These sensitivity analyses were also conducted for the target variables energy consumption and service level. These analyses showed that the service level settles at a value close to 100% even at quite low ranges, which is associated with low shortfall costs. The quality of the values for energy consumption correlates strongly with the service level. This effect can be explained by the fact that for the sensitivity analysis, only the first tow decision variables were rudimentarily examined for the time being and no material reallocations are integrated. Accordingly, products can only be processed, and energy consumed if products are available in stock. Through this sensitivity analysis of the first two decision variables, a corresponding metaheuristic search space for the inventory parameters could already be defined, which limits deficient solution candidates.

The variation of the material allocation to the distribution centers is now to be investigated in more detail, as it is suspected to be a major lever for minimizing the energy consumption. To reduce the computational calculation time a logical correlation was applied to the material reallocation. To investigate different assignments of product and distribution center, a percentage of material reallocations to be performed can be defined before the start of an optimization run. In the initial population and with each mutation of the genetic algorithm, a material is randomly reallocated to on ore more distribution centers according to this ratio.

4 Description of Methodology and Tools

Following the definition of the decision variables and the objective function, the methodological configuration must be designed. Two so-called "Nondominated Sorting Genetic Algorithms" (NSGA-II [13] and NSGA-III [14]) are used as metaheuristics in different experiments, which are based on the principle of genetic algorithms. According to them, the core building blocks are selection, recombination, and mutation.

In contrast to classical evolutionary methods, the two algorithms are particularly suitable for application to discrete multicriteria optimization problems and are accordingly equipped with mechanisms that enable the determination of a Pareto ranking.

Although the NSGA-III, in contrast to NSGA-II, is equipped with a lot of normalization for distance calculation and a Niching mechanism, it does not provide better results for every application. For a more detailed explanation of the algorithms, it can be referred to the corresponding literature.

The metaheuristics are implemented in the Python programming language and coupled to the Tecnomatix Plant Simulation software from Siemens, in which the simulation model was created, using the Component Object Model (COM) interface. The interface makes it possible to control Tecnomatix Plant Simulation from other programs so that they can, for example, start simulation runs, change model parameters and record results.

After the generation of solution candidates in the metaheuristic in Python, these are transferred to the simulation model and then a simulation run is started from Python. The termination of the simulation is communicated via an event in the COM interface, after which the results of the simulation model are transferred to Python.

To increase the computing speed, an additional parallelization of simulation runs on several cores of the CPU was realized. Figure **4** shows the process flow of the simulation optimization roughly by means of a process diagram.

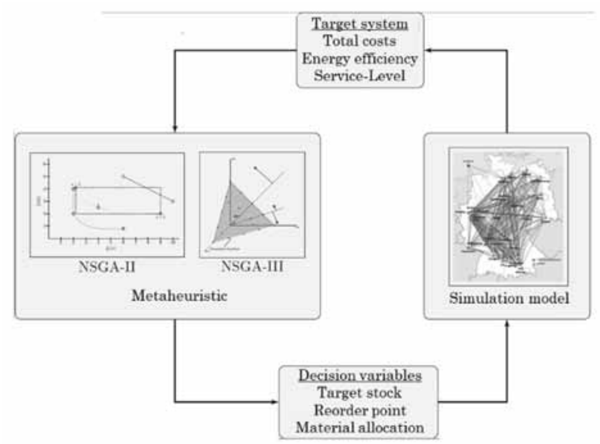

Figure 4: Process diagram of the simulation-based optimization.

5 Results of the Experiments

An experimentation plan was developed for the different algorithms with varying configurations. The design consists of four experiments that investigate the quality of the different algorithms as well as the different proportions of material reallocations (MR) for a given population size (PS). The plan can be found in Table 1.

Experiment	ID	Algorithm	MR	PS	Generations
Experiment 1	EXP 01	NSGA-II	33 %	50	50
Experiment 2	EXP 02	NSGA-II	0 %	50	50
Experiment 3	EXP 03	NSGA-III	33 %	50	50
Experiment 4	EXP 04	NSGA-II	66 %	50	50

Table 1: Experimentation plan.

In this simulation study, a metaheuristic terminates after 50 generations. This results in 2,500 possible solutions from one metaheuristic. To account for stochastic significance, two replications are performed for each experiment. Thus, 5,000 possible solutions need to be evaluated for one experiment. The simulation period is one year per simulation run. The results are shown in a scatter plot in Figure **5**.

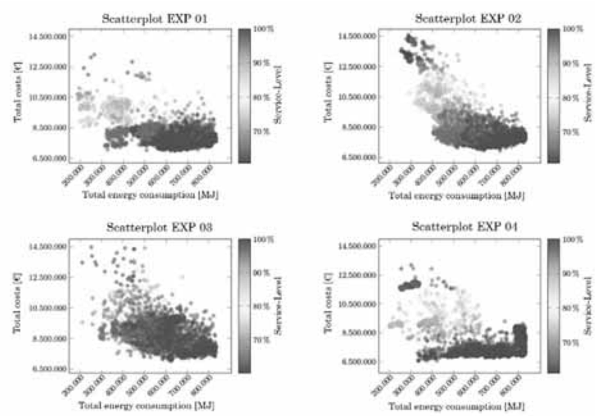

Figure 5: Scatter plots of the objective function values.

Especially in the experiments with a low proportion of material reallocations (experiments 1-3), a roughly linear dependency between the target variables can be seen.

This result can be attributed to the fact that a lower service-level is associated with the fact that the desired production quantity was not achieved and therefore the machines consumed less energy due to less total production quantities. Since shortage costs are integrated into the cost function in addition to transportation, ordering and inventory costs, such candidate solutions incur correspondingly high costs due to poor delivery service with low energy consumption.

With a higher proportion of material reordering, promising solution candidates can be identified that achieve low costs and energy consumption with a good service level. This is possible because distribution centers vary in energy efficiency. Therefore, material reallocations with efficient inventory parameters are identified so that the materials are produced both close to the customer and at energy-efficient locations.

Furthermore, a large spread of resulting points occurs in the cluster for experiment 3. This can be explained by a different selection operator of the NSGA-III algorithm compared to NSGA-II. The pareto sets of the experiments in Figure **6** provide an even more explicit way of interpreting the results.

The most promising pareto set tends to be generated in Experiment 4. Compared to the pareto sets from the remaining experiments, several candidate solutions have both better delivery efficiencies, energy consumptions and overall costs. Many candidate solutions from the pareto set in experiment 4 would dominate large portions of the remaining pareto sets.

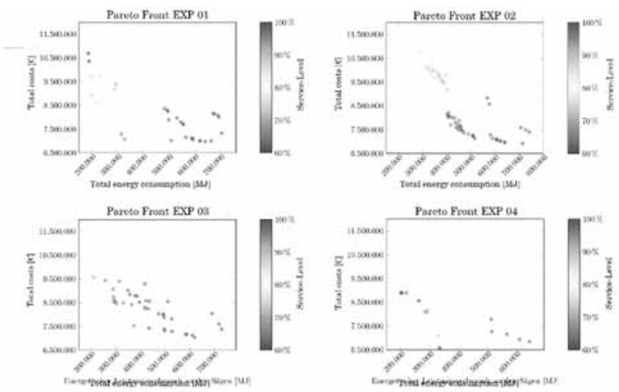

Figure 6: Pareto sets of the experiments.

As anticipated, a single best solution which dominates all three objective functions was not found due to the various trade-off effects within a supply chain.

Nevertheless, recommendations for a course of actions can be derived from the generated pareto sets, depending on the individual weighting of the target system. Experiment 4 delivered solution candidates with total costs of about 6.5 million Euros, a power consumption of about 330,000 MJ and a supply readiness level of about 99 %. Solutions with better energy consumption exist, but the selection of these solutions significantly worsens the service-level as well as the total costs.

Unless individual preferences in the use case overprioritize energy consumption and perfect delivery performance, this underlying combination of decision variables is an extremely eco-efficient configuration for the use case at hand.

6 Summary and Conclusion

The simulation-based optimization for the configuration of eco-efficient supply chains presented in this paper represents a high-performance tool for the generation of target system specific pareto sets. The integration of the target value energy efficiency into a three-dimensional target system supplemented by the dimensions cost and service level in combination with the chosen algorithms and simulation tools represents an innovative approach that stands out from the previous state of the art. Within the evaluation of the experiments, promising eco-efficient configurations could be identified and corresponding assignments of the decision variables for the use case regarding material reallocation, order point and target inventory could be derived. The experiments also made it clear that the NSGA-II algorithm was able to identify better solution candidates than the NSGA-III in the consideration of this use case.

Further research needs to address other methods like reinforcement learning instead of metaheuristics chosen in this paper. Furthermore, the choice of a different simulation tool (e.g., SimPy), which completely avoids animations, could allow a more performant simulation-based optimization. This could potentially generate faster solution candidates. Furthermore, it is possible to integrate additional components of energy consumption, e.g., caused by transportation, into the target system.

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Comprehensive Validation Metrics and Precise Updating of Digital Twins of Production Systems

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Abstract. Despite continuous improvements in modelling, software tools and data availability, simulation projects of production systems still require a lot of manual effort, expertise in various disciplines and time. In many projects the high initial invest for building the simulation model is followed by a rather short period of experimentation and analysis. As production systems have to be adapted at an increasing pace to respond to rapidly changing markets and business environments, simulation models of these systems become outdated earlier, reducing their useful time window. One way to extend this time window would be the implementation of a method of automated comparison with the current production systems and subsequent self-adaption of the model to reality to maintain and even improve its accuracy over time. This approach will be presented and validated at a real world use case. Such an enhanced simulation model can be called a digital twin of the production system.

Introduction

Discrete-event simulation models (DES) permit the in-depth analysis and evaluation of improvement ideas on existing production systems without having to interfere with running production, which makes them a powerful tool for efficiency improvement of production [1]. Yet, in most companies simulation models of production systems are still built and used only in temporary projects [2]. This leads to limited benefits by high initial costs, since simulation models require a lot of expertise and time to be creates and implements and even more to obtain satisfying accuracy.

A longer usability would improve the return on investment of simulation models. But once a model is created, it constantly has to be adapted to changes in the real production system, if it shall be used over the whole life cycle of the production system for ongoing analysis and improvement. Since manual adaption is extremely time consuming, an approach of continuous validation of simulation models and automated updating was developed. Validation is by VDI [2] defined as the "examination of the model as to whether the real behaviour of the modelled system is sufficiently well rendered with regard to the examination target" (part 1, p. 21). The continuous validation and update from real production data turn the simulation model into a real digital twin of the production system [3].

1 Literature Review

1.1 Model generation and maintenance

[4] was one of the first to try semi-automated simulation model generation. His approach primarily uses CAD data in STEP-format (STandard for the Exchange of Product model data) to model the layout of the production system automatically. Focussing more on model parameters, [5] proposed an approach to parametrize a model template, which was developed a-priori by experts, with data from ERP (Enterprise-Resource-Planning) and PDA (Production Data Acquisition) systems and performed an analysis of model convergence to reality.

[6] presented different tools and methods to automatically generate simulation models which help designing a high-automated update process. One important step in this research field is the dissertation of Bergmann [7] which uses the Core Manufacturing Simulation Data standard to create simulation models. [8] introduced the concept of a Self-Adaptive Discrete Event Simulation (SADES) but did not provide an exemplary implementation.

A recent and more elaborate overview of existing approaches is given by [9].

1.2 Data input for simulation models

[10] provide an early discussion of chances and obstacles to automated data input, but IT-systems in production have changed a lot in the last 20 years. [11] shows how automated input data management can lead to time reduction and enhanced performance.

Several models and system architectures have been proposed to model the data exchange between physical and digital production systems. Those models are the foundation of the optimization and updating process of digital twins [12,13]. These works focus on the input side of the digital twin and updating, but do not discuss output validation and related automated update triggering in greater detail. Recent work of [14] presents a use case for data input in a remanufacturing facility.

1.3 Model validation

It exists a broad literature concerning the validation of computer models ranging from general discussion of different statistical tests methods [15,16] over the assesment of the general forecast possibilities in particular domains [17] to finetuning of specific tests in certain domains, for example ecological modelling [18].

There are also various works on the challenge of simulation model validation [19].

A general practical guide for validation was published and applied to two discrete simulation models of manufacturing cells by [20].

1.4 Open research topic

Most of the existing approaches focus on automatic model generation. Some end up in a model translation, where the production system is modelled in a certain modelling style and then translated into an DES, which only decreases the modelling effort, if a model in the original modelling environment already exists [21].

To tackle the problem of the need for initial modelling and because commercial simulation tools permit the easy and intuitive creation of simple models even for beginners, the presented approach chooses a different path: An existing model, which is manually modelled and implemented in a commercial simulation software, shall be enhanced by validation and update modules to turn it into a digital twin, which permits its use over the entire life time of the production system. The hypothesis is that the automated validation and updating can improve the initial models performance in terms of prediction accuracy.

2 Own Approach

The presented approach is explicitly aimed at simulation models of existing production systems, which shall be improved or controlled. It does not work for planning simulation models of production systems, which are not yet existing, since a comparison to reality and real data-based updates are impossible. Nevertheless, the approach can be used to transform planning simulation models into process accompanying simulation models during the building and commissioning phase of the production system.

2.1 Process flow

Production lines evolve over time and thus the input data needed for the simulation model, such as process times, availabilities, quality rates etc., change. Therefore, it is necessary to ensure that the digital twin always stays up-to-date and offers a close representation of reality in a given time period. The presented solution is composed of a two parts iterative process (Fig. 1): the validation and the automated updating procedure. The simulation model itself is built and validated beforehand by simulation experts, following [2].

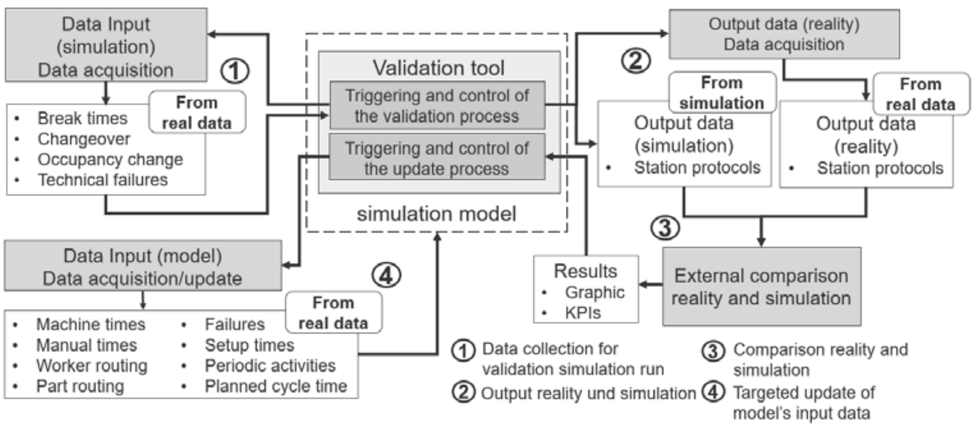

Figure 1: Iterative process of validation and automated updating.

2.2 Validation

The objective of the validation is to automatically compare the simulation model with reality on different levels. The first step is to compare the output of the simulation model and reality by using carefully chosen Key Performance Indicators (KPIs) and boundary values. Further steps are an in-depth analysis using regression analysis.

Deviance measures

To evaluate the deviation of simulation runs to reality, the relative error (see Eq.1) and the NRMSE (Normalized Root Mean Square Error) (see Eq.2) are used. The variation quantifies the final state of production of the studied period whereas the NRMSE quantifies the difference between reality and simulation during the course of the studied period.

$$Relative\ error = \frac{\|N_{real} - N_{Sim}\|}{N_{real}} * 100 \qquad (1)$$

with N_{real} ,N_{sim} being the total amount of produced part at the end of the studied period respectively in reality and in simulation.

$$NRMSE = \frac{1}{\bar{x}_{real}} * \sqrt{\frac{\sum_{i=1}^{N}\left(x_{real,i} - x_{sim,i}\right)^2}{N_{real}}} \qquad (2)$$

with $x_{real,i}$ and $x_{sim,i}$ representing the total amount of produced parts at each point in time t_i of the studied period, respectively for reality and simulation.

Another possibility to measure the prediction error of the simulation model is Theil's U2 (see Eq.3) which becomes 0 for a perfect prediction and 1 if equal to the naïve prediction [22]. When using Theils U2 it is important to know that big prediction errors have a greater influence on the metric [23].

$$U_2 = \frac{\sqrt{\frac{1}{T-h}\sum_{t=h+1}^{T}(x_{sim,t} - x_{real,t})^2}}{\sqrt{\frac{1}{T-h}\sum_{t=h+1}^{T}(x_{real,t})^2}} \qquad (3)$$

Regression analysis

To get an even better understanding of the behaviour of digital twin and reality, it is also helpful to look at the linear regression fit of actual versus predicted values [24]. One important parameter to measure the difference between the simulation and real system using this regression approach is R² [25].

$$R^2 = \frac{\sum_{i=1}^{n}(\widehat{x_i^{real}} - \overline{x^{real}})^2}{\sum_{i=1}^{n}(x_i^{real} - \overline{x^{real}})^2} \qquad (3)$$

The regression fit can also be described using the intercept (a) defined in Eq.4 and the slope b (Eq.5) of the regression line. For a perfect fit the slope would be 1 and the intercept would be 0.

$$a = \overline{x^{real}} - b * \overline{x^{sim}} \qquad (4)$$

$$b = \frac{\sum_{i=1}^{n}(x_i^{sim} - \overline{x^{sim}}) * (x_i^{real} - \overline{x^{real}})}{\sum_{i=1}^{n}(x_i^{sim} - \overline{x^{sim}})^2} \qquad (5)$$

Consequences of validation

If the model output values deviate from the real output less than a predefined degree, it means the digital twin satisfies the expectations and represents the reality to a satisfactory extent. In the case that outputs do not match, input values of the digital twin have to be examined in order to differentiate between input parameters that are still up-to-date and obsolete ones. According to these analysis results, the automated updating will be triggered precisely for the relevant parameters.

2.3 Update

In order for the automated updating process to be efficient, two prerequisites have to be fulfilled. A digital twin where the most effective input parameters are characterized as well as a data pipeline between data sources and simulation system are indispensable. Furthermore, the automated updating process allows replacing outdated data.

Once the update is performed, a simulation run is realized and the validation process is repeated to check the validity of the updated model. The whole process is repeated until the output is within the boundaries or until the digital twin cannot be further improved. In this case feedback is given to the user that an appropriate level of closeness could not be reach automatically and a manual intervention is necessary.

An important outcome of this iterative process is to choose an appropriate time period for the data acquisition, that consequently gives the best compromise between data meaningfulness and acquisition effort while satisfying the performance criteria of the digital twin.

3 Use Case

The described approach was developed in a research partnership between of the wbk Institute for Production Science at the Karlsruhe Institute of Technology (KIT) and the central department Connected Manufacturing of the Bosch Powertrain Solutions division with the goal to develop an agile production system. Its application and validation are also part of this joint research project.

3.1 Production system

The exemplary production system, for which the digital twin is implemented, assembles car engine components in high volume and is composed of two areas which are connected via a conveyor. The two areas are assembly and testing, each semi-automated, following the Chaku-Chaku principle. This means that the machines perform their processes mainly in an automated manner and the workers are primary required for loading and unloading of machines and transporting parts between them. The line produces various product types with differing material flows, processing times, etc. The number of workers in each area varies due to external factors as vacations, sick days, reduced customer demand, trainings, etc. This has to be considered in the validation of the model. Historic production data from various sources is stored in a central data lake, including process times, change over delays, machine failures, scrap rates, etc. The software "Tecnomatix Plant Simulation" by Siemens is used to implement the digital twin.

3.2 Implementation

Using the approach described above, a validation tool that enables the validation and automated updating process is implemented. Before running the simulation model, the validation has to gather information about the system status at each point of time of the validation period from existing information systems such as manufacturing execution systems (MES) and enterprise resource planing (ERP) systems. This includes the number of workers, produced product types and exceptionally long downtimes (more than one hour), that appear very rarely. If the simulation run would not consider this information, its comparison to reality would not be meaningful. The information about the number of workers in the production system at a certain period in time is not stored in the data lake, but in a different IT-System which is not accessible and therefore has to be added manually.

A python script preprocesses the real and simulation output data and compares them automatically. In the use case the chosen characteristic KPIs are: the progression of produced parts over time, the variation of the hourly Overall Equipment Effectiveness (OEE) as well as the total OEE within the analyzed time period. These KPIs give an overview over the systems performance and keep track of the behaviour of the digital twin during the whole simulation run. The permitted deviation of each KPI is decided on accordingly to the company's performance goals and the systems inherent fluctuation. In the use case, the corresponding threshold of permitted deviation shall not exceed 3% for the relative error and 5 for NRMSE.

If the validation process results in higher deviations, another Python script performs the automated update by directly accessing the IT systems and data warehouses to obtain the latest input data. The data pipeline is composed of SQL queries and then filtered and processed into exploitable update data for the Plant Simulation software.

4 Results

Four experiments were conducted on three different weeks of production. The first experiment validates an input data set and the model`s behaviour with the basic KPIs and their static thresholds, while the second experiment provides an in-depth analysis of the behaviour using more advanced regression and statistical KPIs. The third and fourth experiments highlight the use of an automated targeted update to correct the input data and enable a better fitting of simulation with reality.

4.1 Automated validation

The first experiment was conducted for a production period of one week. To model the non-deterministic behaviour of the simulation, five simulation runs with different random seed values were conducted for each experiment with Plant Simulation Tecnomatix to get a statistical confidence of the results. Those five runs were considered sufficient as they well reflect the statistical repartition of the model while ensuring an acceptable optimized run time of the experiment. The automated validation compares each simulation run with reality and on the one hand returns graphs (Figure 2) to help the user visualize the part's production during the production period. On the other hand, it generates key values to quantify the production systems behaviour (Table 1).

Figure 2 shows a good fit of line output between the simulation runs and the reality for both the assembly and testing lines. This visual analysis is confirmed by the calculated key values from Table 1. The mean variation for both lines is under 3% and the mean NRMSE is under 5.

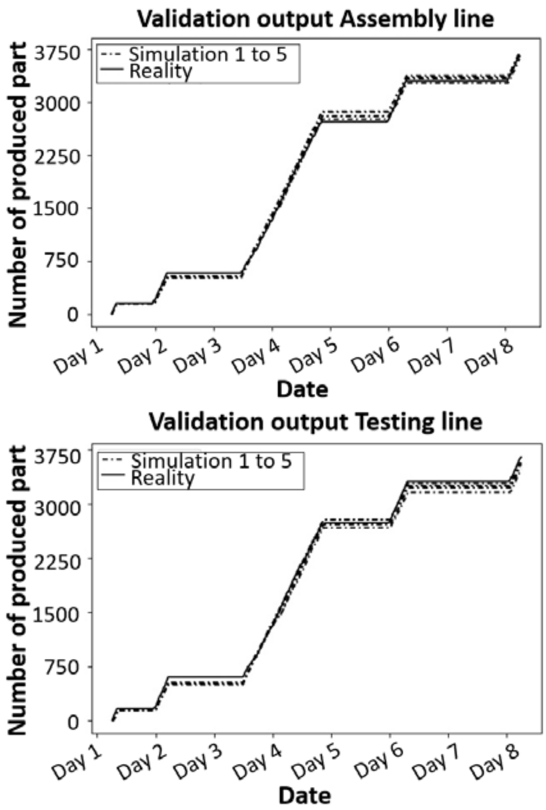

Figure 2: Validation output of assembly and testing line – experiment 1.

Line	Produced parts reality	Mean produced parts simulation	Mean Variation (%)	Mean NRMSE
Assembly	3650	3677	1.13	2.69
Testing	3639	3545	2.58	3.57

Table 1: Results of automatic validation.

The fixed criteria from Section 3.2 are therefore fulfilled and the input data is considered still up-to-date. The focus of the analysis lies on the number of produced parts since the OEE follows this number linearly.

4.2 In-depth analysis

The second experiment focuses on an in-depth validation of another week which has a different production plan with different product variants and different production breaks. The visual analysis in Figure 3 already indicates a good fit between the curves of reality and the simulation runs. When we are now looking at the mean deviation of overall output, we see that it is 2.0% and 1.64%, which is lower than the defined thresholds, therefore the validation is positive according to this indicator. The NRMSE is 4.55 for assembly and 4.82 for testing, which also indicates a good fit of the model given the threshold of 5.

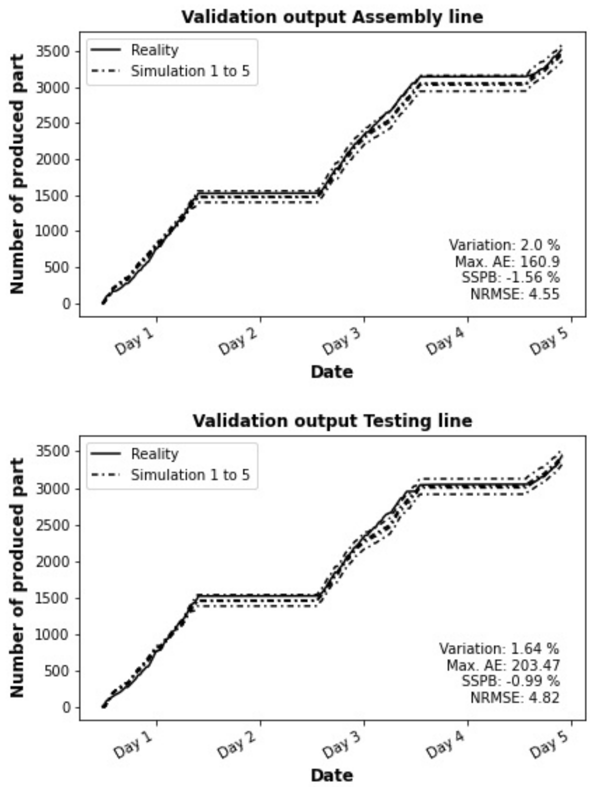

Figure 3: Validation output of assembly and testing line – experiment 2.

Figure 4 shows the regression analysis of experiment 2 including the related parameters for assembly and testing. R^2 reaches with 0.86 and 0.9 quite high values which expresses a good fit of the simulation model to reality as well. The slope is in both cases very close to 1 which is another indicator that the model in general provides a good estimation for the behaviour of the real system. The intercepts are 0.56 and 0.96 which is also a good value considering the absolute scale of the axis ranges from 0 to 100.

Therefore, the regression analysis underlines the positive validation result of the subjective visual impression and the basic deviation analysis. Theil's U_2 is 0.52 and 0.54 respectively which also indicates a good fit.

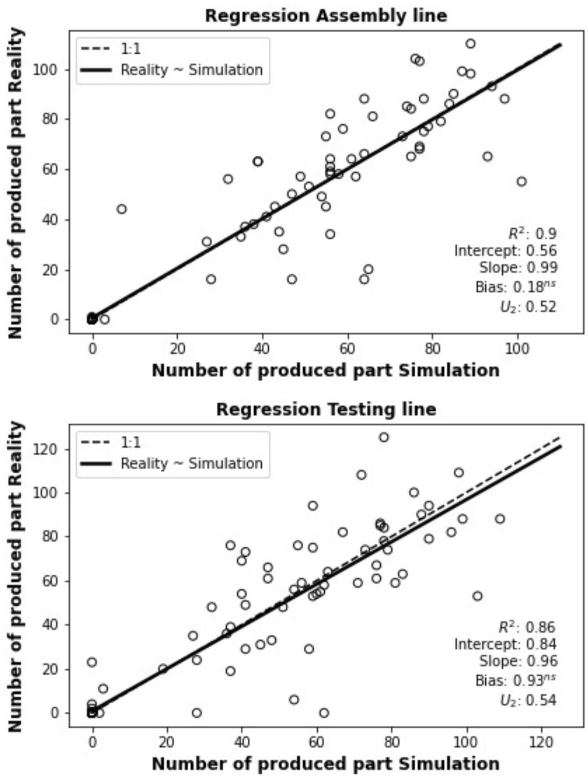

Figure 4: Regression analysis of testing and assembly line - experiment 2.

4.3 Targeted update of the input parameters

For the third and fourth experiment, simulation and validation were conducted for another week of production. In the third experiment, the same input parameters as in Section 5.1 were used. However, the obtained results before any update (Table 2, Figure 5) from the validation process exceeded the fixed threshold.

Therefore, an update of input parameters is triggered. The first step of the update process is to determine which data must be replaced and if the line is partially or totally concerned by the update. The mean relative error on both assembly and testing line are bigger than 3%, furthermore the NRMSE of the testing line is above 5. Consequently, both lines have to be updated.

Among the input data, it is possible to update the following parameters: Part routing, worker routing, failures, machine process times, manual process times, setup time and planned cycle times.

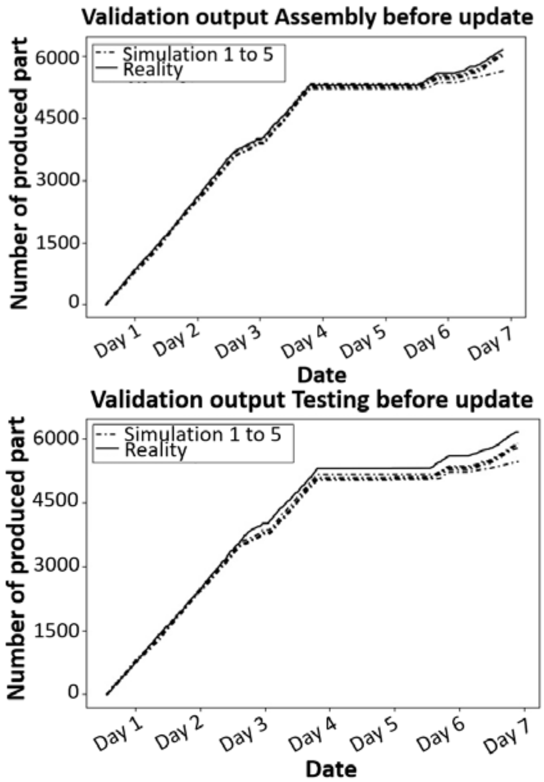

Figure 5: Validation output before update on assembly and testing line – experiment 3.

Nonetheless, among those parameters few register notable deviation during the chosen time period. In this paper, the focus was put on the machine process times, which encountered consequent variation over the studied week. After recalculating the probability density function of the machine process times from real data with a python script, the targeted update process compares the new calculated values with the old values for each machine. The machine process times are modelled by a normal distribution through mean and standard deviation. If the mean differs more than 0.15 seconds and the standard deviation more than 0.2, the old value is replaced with the new value. As mentioned above, in this use case the other input data did not change significantly and did not need any update.

Once the input parameters are updated, a fourth experiment with the newly calculated input data is conducted. Figure 6 depicts the output validation after the update for assembly and testing lines. Figure 6 shows improvement compared to Figure 5. The behaviour of the simulation is closer to reality and shows less variability. Those observations are verified through the key values in Table 2. For the assembly line, the mean relative error of simulation went down from 3.03% to 0.92% and the mean NRMSE went from 2.99 to 1.77.

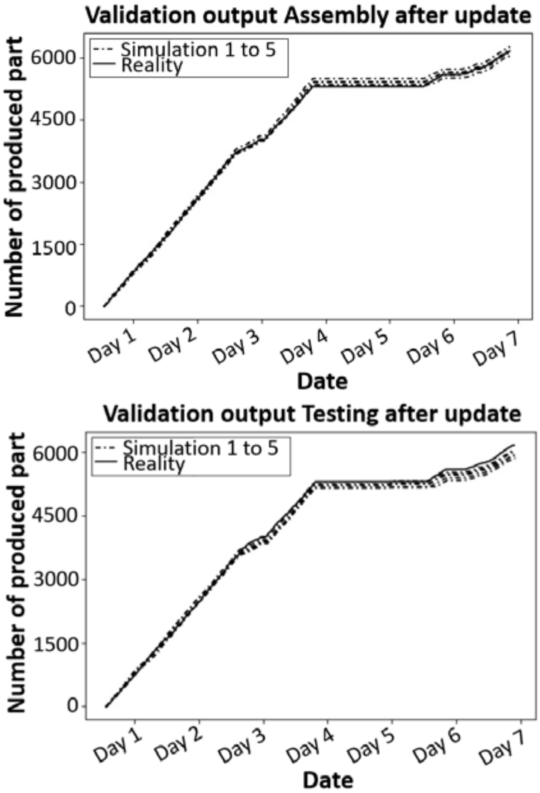

Figure 6: Validation output after update on assembly and testing line – experiment 4.

The capability of the targeted update process was nonetheless proved but still needs further improvement particularly concerning the threshold values and the trigger conditions for the targeted update mechanism.

Experiment	Line	Mean difference (%)	Mean NRMSE output	Validation passed?
Before update	Assembly	3.03	2.99	No
After update	Assembly	0.92	1.77	Yes
Before update	Testing	6.32	5.69	No
After update	Testing	3.2	3.22	No

Table 2: Validation metrics before and after automatic update.

For the testing line the mean relative error went down from 6.32% to 3.2% and the NRMSE from 5.69 to 3.22. A net improvement is indeed realized.

The behaviour of the assembly line is now completely validated whereas the testing line still has a mean relative error barely above 3%. But the NRMSE has been improved and is now below 5. The machine process times could not be further improved for the testing line. In a next step, other parameters of the simulation models, i.e. availabilities, scrap rate, etc. should be updated. For these parameters an automated update process is not yet implemented.

5 Conclusion and Outlook

Motivated by the ever-changing structure of modern production systems, an approach to enable simulation models to mirror these changes was developed. The approach contains a module for continuous validation which compares simulation KPIs to real historic KPIs. Various metrics to measure the deviation of the simulation to reality for this validation module where discussed and implemented ranging from simple deviation KPIs to more complex statistical and regression values. If a certain deviation threshold is surpassed, this module triggers an automated update module which changes the simulation model to better reflect reality.

The application of this approach at a semi-automated production line of automotive components leads to a convergence of the simulation model to reality, turning it into a digital twin.

Further research has to be done to evaluate the behaviour of the digital twin in different scenarios of changes in the production system as well as its robustness to incomplete and/or biased data. This includes the further study of the behaviour of the various reality metrics introduced to this paper. Another line of research would be the extension of the available update mechanism of the digital twin. This could be combined with a thorough examination of the validation KPIs and their thresholds.

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Simulation-based Assessment of Energy Demand and Costs Associated with Production Scrap in the Battery Production

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Abstract. The shift in the mobility sector towards electric vehicles is responsible for a growth in the market demand for lithium-ion batteries. To follow this trend, the current 200 GWh global production capacity of lithium-ion batteries will present an annual increase of up to 300 GWh in the next years. Characterized by an energy-intensive process chain and high material costs, battery production is sensitive to production scrap rate. Current works on energy and cost assessment in battery production consider scrap rates based on static values derived from historical production data. Thus, there is a lack of works that dynamically analyse the influence of different scrap rates on the process chain, e.g. considering machine states and utilisation capacity. To tackle this challenge and contribute to more sustainable and competitive battery production, this work presents a simulation-based methodology to assess the indirect and direct energy demand and costs associated with production scrap.

Introduction

Lithium-ion batteries offer a wide range of applications, with the mobility sector accounting for more than 60% of the 200 GWh global demand in 2019. To follow the electromobility growth, studies predict that the global capacity of production of lithium-ion batteries will present an annual increase of up to 300 GWh in the next years [1].

Due to its energy-intensive process chain, manufacturing is responsible for up to 45% of the battery cradle-to-gate environmental impacts [2]. Besides the environmental impact, production is also the main cost driver. Here material is a decisive aspect, accounting for up to 70% of the costs of a single battery [3]. Therefore, a more environmentally sustainable and cost-competitive battery cell production depends on material and energy-efficient production. The reduction of production scrap, i.e. material waste intrinsic to the process or resultant from material flaws, increases the material efficiency and reduces the production costs. However, reducing the scrap close to zero requires sophisticated strategies and significant investments [4].

For large-scale production, production scrap rates vary from 5 to 10% [2]. Different works in the battery production context with a focus on energy efficiency [5–7] and cost estimation [8–10] consider production scrap in their models and calculations. Nevertheless, there is a lack of works that dynamically analyse the influence of different scrap rates on the process chain, e.g. considering machine states and utilisation capacity. Simulation-based approaches represent a well-established tool for understanding complex relationships and dynamics of process chains and have already been applied in the analysis of material and energy flows as well as production improvements [6,11].

Against this background, this work proposes a combined discrete event and agent-based simulation approach to (i) dynamically study the effect of different scrap rates on a process chain level and (ii) provide identification of critical processes from energetic and economic perspectives.

1 Theoretical Background

1.1 Lithium-Ion Battery Production

The battery cell production is characterized by a rigidly interlinked process chain with numerous heterogeneous process steps. In general, the process chain can be divided into electrode production, cell production, and cell conditioning. However, slight variations might occur in the battery process chain depending on the respective process technology and the battery cell design, e.g. pouch, cylindrical or prismatic. In electrode production, anodes and cathodes are produced in batch and continuous processes, located in separate production lines to avoid contamination [9].

After a dry and wet mixing process, the respective material suspension is coated and subsequently dried to produce a composite structure. Afterwards, anode and cathode coils are calendered to reduce their porosity and slit to width and length before they enter the dry room for cell production, characterized by discrete processes. First, the coils are further cut into single electrode sheets. For pouch cells, the individual electrode sheets are stacked together with a separator. The electrode-separator assembly is contacted internally and afterwards inserted into a pouch bag housing. The housing is then filled with electrolyte and subsequently sealed. In cell conditioning, the formation and aging of the battery cells are conducted [3].

Scrap rate information in the literature is diverse and limited, usually derived from input-output rates and historical data. Based on previous publications, Drachenfels et al. (2021) present variations in scrap rates according to production scales, e.g. 5 to 20% for small and 5 to 10% for large factories [2]. Nelson et al. (2019) present process-specific scrap rates, varying from 1 to 8% according to the process characteristics [8]. Schünemann (2015) proposes even lower rates, e.g. 1% for the mixing process and 0.2% for stacking [9]. Production scrap rate has also a major influence on production energy demand and costs.

Energetic Perspective. The battery cell production requires a significant amount of electrical energy, especially caused by its energy-intensive processes, e.g. coating/drying, calendering, and formation [5]. In addition, the technical building services (TBS), which provide the necessary environmental conditions, also contribute to a significant share of the total energy demand [12].

The literature reports large variations in energy demand per energy storage capacity at an industrial scale, ranging from 47 to 162 Wh per Wh [7]. These variations can be explained by the production scale, the complex and dynamic combination of continuous and discrete processes as well as the selected process parameters and boundary conditions [2,13].

The assessment of energy considering scrap rates has been shown in different works. Thomitzek et al. (2019a) present a material and energy flow analysis based on input-output ratios and the measured energy demand [5]. Weeber et al. (2020) propose a simulation on process chain and process levels to assess the overall energy demand [6]. Wessel et al. (2021) provide an analysis of energy demand due to scrap for a pilot line based on production data [12]. The results show critical energy-intensive processes when analysing energy demand associated with scrap. Although the scrap rate has been considered in many works, it was usually limited to static average values based on production data. Thus, it is necessary to dynamically analyse the influence of scrap rates in battery production on the energy demand.

Economic Perspective. Material costs represent the largest share of battery production costs. Kwade et al. (2018) present in a cost breakdown that 74.9% of the costs are caused by material and 3.1% by energy demand [3]. Duffner et al. (2021) show the share of the various costs for an optimization scenario with materials (77%), machine depreciation (8%), production scrap (6%), and energy (3%) being the largest ones [14]. Due to the importance of material efficiency for more competitive production, production scrap has been considered in different cost estimation models. A simulation-based approach to assess the importance of economy of scale on production costs is presented by Mauler et al. (2021) which considers production bottlenecks and end-of-line scrap rates [10]. Concerning process-specific costs, Kwade et al. (2018) declare that processes further down the process chain are more cost-sensitive since they embody the value added by the previous processes [3].

Duffner et al. (2021), on the other hand, mention an electrode production process (coating) as critical [14]. The review on cost models presented by Duffner et al. (2020) lists many works which consider process-specific parameters in their estimations [15].

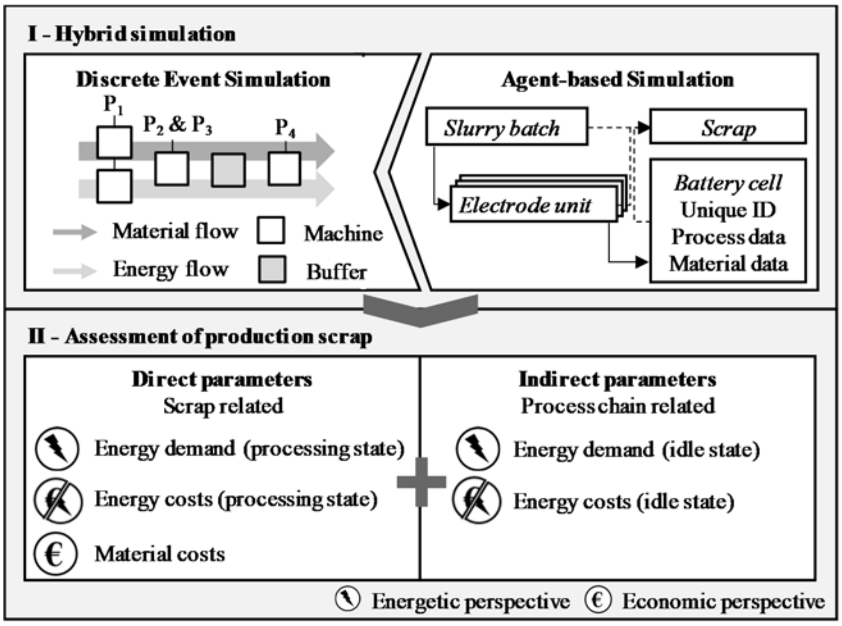

Figure 1: Simulation-based methodology to assess the effects of production scrap on the process chain.

Therefore, there is a lack of work with focus on the production scrap rate and its influence on the process chain.

However, none of them dynamically analyses the process chain when defining scrap and energy-related costs. Based on the relevance of the material efficiency to the battery cell costs, it is fundamental to consider the economic influence of different scrap rates.

1.2 Simulation Approaches for Process Chain Analysis

Simulation is a consolidated approach to analyse different production scenarios and process chain performance [11]. In the battery production context, it has also been identified as an effective tool to assess and analyse energy demand for different production and machine configurations [6,13]. Discrete event simulation (DE) enables a better understanding and reproduction of material and energy flows within the production as well as provides insights on dependencies between processes. Agent-based simulation (AB) enables to describe elements, e.g. machines or products as a unique agent, study their interactions, and store specific data. The use of DE and/or AB to analyse production throughput, machine availability, and process-specific energy demand in the battery context was already proposed by different works [6,11,13]. When considered, scrap rate is described as a process characteristic based on static data to support analysis of input and output flows between processes.

2 Methodology

A simulation-based methodology was developed to study the influence of different production scrap rates on the process chain dynamics with a focus on energetic and economic perspectives, as described in Figure 1.

2.1 Hybrid Simulation

The first methodology part is a python-programmed hybrid simulation that combines DE and AB approaches. The focus of the DE is to reproduce the material and energy flows along the process chain, consisting of the following elements: machine, process, and buffer.

A process can be executed by more than one machine and a machine can be assigned to more than one process. In addition, it is possible to have buffers to store finished parts. Otherwise, the finished part is temporarily stored in the machine, until it is taken to the next process.

A machine presents five states: off, ramp-up, idle, processing, and failure. Off is the machine state either at the beginning of the simulation or after breakdowns. The ramp-up state starts after the machine is switched on until it is ready to produce. A machine is in idle state before processing, i.e. waiting for input material and machine availability. The processing state represents the production itself and, in some cases, the storage of finished parts. Lastly, a machine may break during processing. Average power consumption and duration of each machine state are inputs defined by the user. An overview of the conditions for state changes and power consumption over time are shown in Figure 2.

The conditions for each state change are represented in Figure 2a. With exception of the off state, all state changes are triggered by an event. Ramp-up and failure events are time-regulated, based on the user inputs regarding the average and variation of the process duration. The processing state is time-regulated and additionally considers the storage of finished materials. The idle state is controlled by two events: input and machine availability.

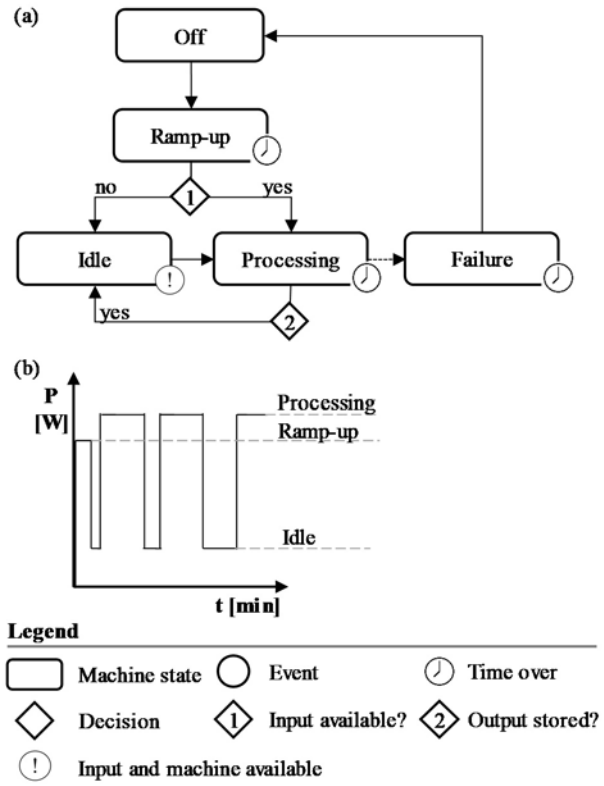

Figure 2: (a) Machine state chart and (b) machine energy profile based on the duration and average power consumption of the different states.

The last condition is especially relevant for machines associated with more than one process. The timestamp of changes in the machine states as well as power consumption values result in the energy profile shown in Figure 2b.

The AB simulation focuses on the agents, e.g. slurry batches, electrodes, and battery cell.

During the simulation, agent-specific information regarding the process (e.g. timestamp and energy demand) and the material (e.g. input, output, and scrap ratios) is stored. The interaction between agents is achieved by the possibility to combine them. For example, a battery cell contains various cathodes, these cathodes originate from the same slurry batch.

The agents are either located in a buffer or a machine, which provides the integration of both DE and AB approaches. A timestamp is stored whenever a state change in the DE triggers a change in the agent location change. Further process and material-specific data, e.g. scrap and output amount as well as energy demand are also stored within each agent.

The integration of both simulation approaches provides knowledge regarding the conditions under which each agent is produced and the associated energy demand. The main program functions responsible for this integration are described in Figure 3.

Scheduler is one of the main functions, responsible for initialising the machines at the simulation start. It is also called before and after processing to check the machine and input availability. The acquisition of input material and storage of finished parts are executed by the *inventory_get* and *inventory_put* functions. These functions are based on the Python package SimPy which enables an allocation of materials in a virtual container and provides, for example, the possibility to wait until the material is available.

Lastly, the functions *agent_get*, *agent_put*, and *agent_update* support the AB simulation by managing the creation and location of agents as well as data storage.

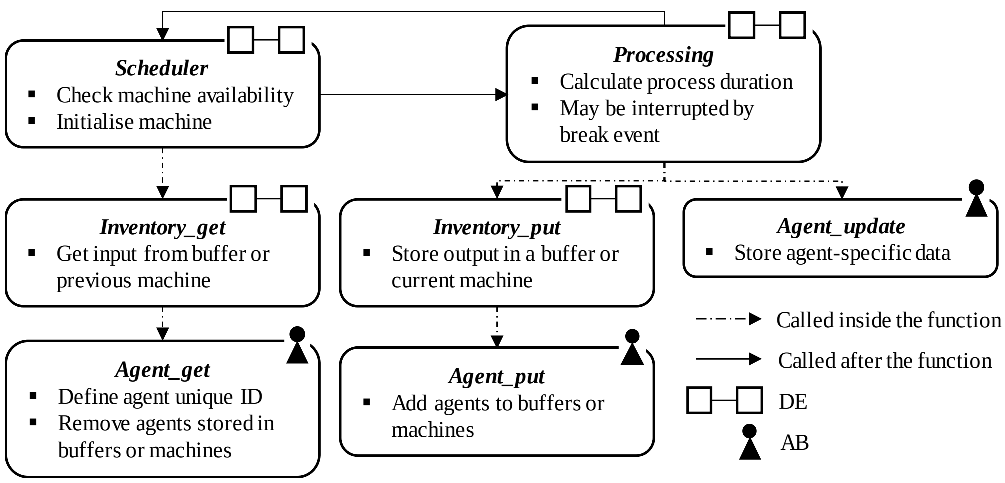

Figure 3: Program main functions for the DE and AB simulation approaches.

2.2 Assessment of Production Scrap

The simulation results are used to assess the energetic and economic influences of different production scrap rates, considering direct and indirect parameters. Different power consumption values are associated with the machine states ramp-up, idle, and processing. Energy demand during processing results from the average consumption and process duration, and may, therefore, be directly associated with a scrap agent. As consequence, energy demand during the processing state is classified as direct parameter. Parameters affected by scrap on a process chain level are classified as indirect. Production scrap may cause, for example, changes in the material flow and affect the duration of waiting times and energy demand of machines. Therefore, energy demand in idle state is considered an indirect parameter. In battery production, TBS is a major energy consumer, responsible for maintaining adequate production conditions. Since these conditions must always be achieved, independently of the throughput and scrap rate, TBS energy demand is constant and, therefore, not considered in this assessment.

A complete estimation of production costs includes fix and variable costs. Fix costs are associated with investments (e.g. machine acquisition), building, maintenance, and overhead. Variable costs comprehend material, energy, and labour. Since the fixed costs are strictly dependent on the production scale and are constant regardless of the production throughput and scrap rates, they are not considered in this work. Moreover, for constant working hours and number of shifts, labour costs also remain the same. Thus, material and energy are the only costs considered in this assessment. Material and processing energy costs are classified as direct since they are calculated based on agent-specific information, e.g. amount of scrap and energy demand. Indirect parameters comprehend the ones affected by scrap on a process chain level, i.e. energy costs related to idle states.

3 Use Case: Battery Cell Production

The proposed methodology was applied to the pilot line of the Battery LabFactory Braunschweig (BLB). The energy and process parameters to produce a 10-compartments pouch cell were automatically acquired via the SCADA system described by Turetskyy et al. (2020) [16].

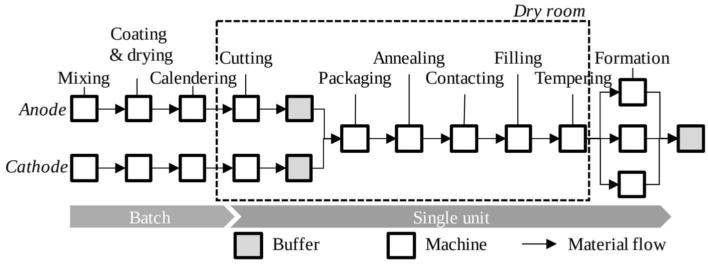

Figure 4: Simulated processes adapted from the BLB production line.

Since material prices for a pilot line are not consistent with the ones for a larger production scale, this use case considered the prices described in the BatPac cost model [8]. An around-the-clock production with the BLB machine capacities was simulated to investigate the dependencies and dynamics between processes, e.g. share of each machine state as well as material and energy flows. Moreover, differently from the BLB pilot line, the simulation considered separate production lines for cathode and anode production, as shown in Figure 4.

First, a one-month production with no scrap was simulated as a base scenario. Subsequently, the simulation was repeated in four scenarios with scrap rates ranging from small to large scale productions (1%, 5%, 10%, and 15%). In each scenario, the same scrap rate was considered for every process which represents, for example, a yield of 90.4% for the 1% scenario. For batch processes, scrap is a share of the produced batch. For single unit processes, scrap represents an entire unit.

The simulation results of all five scenarios were assessed according to the direct and indirect parameters described in the methodology. First, the influence of different scrap rates was evaluated by assessing the *direct parameters*, i.e. the scrap-related energy demand as well as energy and material costs.

Figure 5 presents the average material and energy costs associated with scrap per finished battery cell for each simulated scenario.

As expected, a scrap rate increase is directly related to higher material and energy costs associated with scrap to produce one battery cell. However, this increase is not proportional to the scrap rate and affects differently the energy and material costs. For the 1% and 5% scenarios, the energy costs are slightly higher than the material costs. For the 10% and 15% scenarios, material costs become more significant.

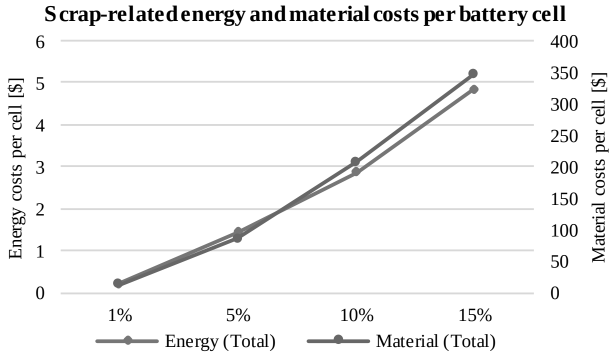

Figure 5: Scrap-related energy and material costs to produce one 10-compartments battery cell for the different simulated scenarios.

		Scrap-related costs per cell [$]		
		Energy	Material	Total
5% scrap rate	C. Mixing	0.001	0.192	0.193
	C. Calendering	0.003	0.022	0.025
	Formation	0.194	12.206	12.400
15% scrap rate	C. Mixing	0.011	2.380	2.391
	C. Calendering	0.027	0.242	0.269
	Formation	0.585	38.567	39.152

Table 1: Comparison of the scrap-related costs for selected processes considering direct parameters (energy and material costs) for 5 and 15% scrap rates.

A closer look at the process-specific costs shows that some processes are more critical from an energetic perspective, while others present significant material costs. The production type (batch or single unit) also plays an important role in the intensity of the scrap effect at each process.

Moreover, cathode and anode production present different variations, since cathode production is more intense from both energetic and material perspectives. Table 1 exemplifies the process-specific variations for one produced battery cell based on three selected processes (cathode mixing, cathode calendering, and formation).

Considering the selected processes of the cathode production, calendering is the most critical one from an energetic perspective while mixing is the most critical one with regard to material costs for both the 5 and 15% scenarios.

Since cathodes are produced in batches, the energy and material costs related to one battery cell (containing 10 cathodes and 10 anodes) are significantly lower than the costs incurred in the single unit processes of cell production, e.g. formation. Regarding the total costs, the most critical processes for both scrap rates are cathode mixing and formation. Furthermore, a comparison of the variations between the 5% and 15% scenarios shows that the total cost of mixing increases by a factor of twelve while the formation total costs by a factor of three.

In a second step, the influence of scrap rate on a process chain level was evaluated by measuring the variation of *indirect parameters* for each scenario. The energy cost for the entire process chain was calculated based on the energy demand [kWh] in idle state for a finished battery cell and the electricity price for business in Germany of 0.237 $ per kWh. To provide better identification of the variations for each scenario, the share of costs for idle and processing states are compared in Figure 6.

The results of Figure 6 reinforce that a variation in the scrap rate is responsible for dynamic changes in the process chain, e.g. duration of machine states. Since the processes are rigidly interlinked and the throughput of each single unit process is reduced by an increase in the scrap rate, processes down the process chain have to wait longer for input material. This increase in waiting times leads to higher idle state costs. The reduction of throughput at each single unit process also leads to fewer processed parts in one month and, consequently, to a reduction in processing times and costs. It is also important to emphasize that these effects are not proportional to the scrap rate: in comparison to the base scenario, the share of costs in the idle state increases by 1.8% and 10.2% for the 1% and 15% scenarios, respectively.

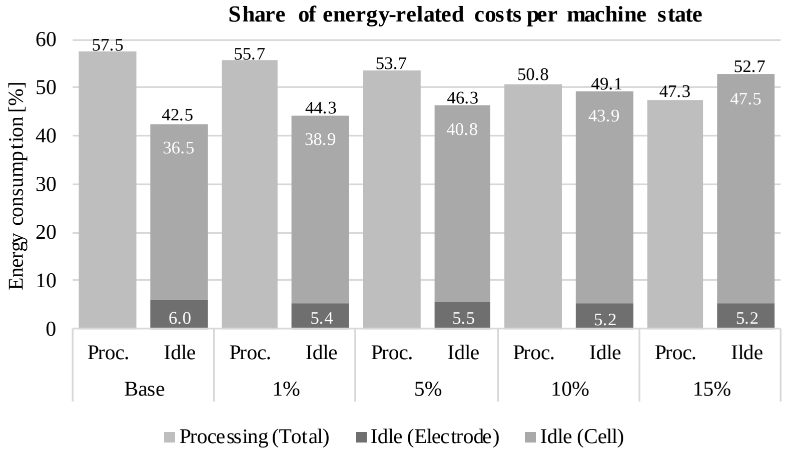

Figure 6: Costs associated with energy demand in idle and processing states per finished battery cell for different scrap rates.

The share in idle states also differs between the electrode and cell production. As shown in Figure 6, the share in idle state for electrode production decreases at higher scrap rates. Since scrap in the electrode production leads to a reduction of the batch size, processes whose duration depends on the material quantity (e.g. coating and calendering) present shorter processing times and, consequently, lower idle times. As previously mentioned, single unit processes need to wait longer for input from the previous processes, therefore, presenting a higher share in idle state at higher scrap rates.

Overall, the results show that different scrap rates have dynamic effects on the process chain, altering the material flow and the shares in processing and idle times. An analysis on the process level shows that processes are affected differently from both an energetic and economic perspective. The intensity of these effects is influenced by the process type (e.g. batch or single unit), position in the process chain, material costs, and energy demand.

4 Summary and Outlook

Material efficiency is fundamental for more cost-competitive and environmentally sustainable battery production. Current works on energy and cost estimations consider production scrap rates as static values derived from historical data and do not assess their dynamic effect on the process chain.

To tackle this challenge, this work proposed a simulation-based methodology to dynamically study the effect of different scrap rates on a process chain level and provide the identification of critical processes from an energetic and economic perspective. First, a discrete event and agent-based simulation was used to study the material and energy flows of one-month battery production. The results for different scenarios were analysed with a focus on parameters with direct relation to production scrap (e.g. material costs and processing energy).

In addition, the effects of production scrap on a process chain level were assessed based on indirect parameters (e.g. energy demand and costs for idle states). The results demonstrated the importance of dynamically assessing the effects of scrap rates since they differ for each process and are influenced by various factors, e.g. process characteristics, position in the process chain, material costs, and energy demand.

Future works will study the effect of process-specific scrap rates to define acceptable tolerances and support the planning of quality gates.

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Demand-Driven Supply of Offshore Wind Turbine Components by Cascading Simulation and Optimization

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Abstract. The installation of offshore wind farms constitutes a highly weather-dependent process. Despite this dynamic, practice and research generally assume fixed resupply cycles to deliver components from their production sites to the installation's base port, resulting in high storage requirements. This article proposes a cascading discrete-event simulation framework combined with offline mathematical optimizations to decide demand-driven on suitable resupply cycle from a pool of routes. This approach combines the advantages of both methods by allowing high flexibility to cope with weather dynamics while reducing the search space to a few optimal alternatives. The evaluation uses two real-world use cases. It demonstrates that selecting cycles based on estimated weather developments reduces the required base port storage capacity. Moreover, in some cases it additionally maintains lower capacity levels after an initial ramp-up phase.

Introduction

Over the last years, wind energy has developed into a primary green, sustainable energy source. Since 2010 the installed capacity of offshore wind farms has increased exponentially, from 2.9 Gigawatts to 35 Gigawatts in 2020 [14]. Moreover, over the last years, most countries increased their targeted shares of renewable energy or moved forward their targeted dates [14].

Compared to their onshore counterparts, offshore wind farms allow for higher capacities due to larger accessible areas at the open sea and higher wind speeds. Nevertheless, the same advantages result in additional challenges for installing such wind farms, e.g., due to harder to reach installation sites, stronger winds and weather dynamics, and more expensive resources [16].

High wind speed poses a challenge for installation operations at the open sea. Due to the sheer size of turbines, installations require crane operations in approximately 100 meters of height. Thereby, high waves or wind speeds result in sways of several meters, rendering installations unsafe for the crew, components, or even the vessel and crane. Consequently, installation operations have defined limits considering these parameters. Rippel et al. (2019) [16] provide an overview over such limits assumed in the literature. Generally, weather conditions at the open sea tend to change quickly due to the large open area. In contrast, planners can only rely on forecasts or historical records and their experience when planning installations, which introduces high uncertainties, especially during the installation's operative phase. Literature attributes between 15% and 30% of a wind farm's overall costs to logistics costs during the installation resulting from this uncertainty and the costly resources involved in installations (e.g., [5, 11]).

Most of the literature that considers offshore installations focuses on efficient scheduling of vessels, fleet mixes, or viable project start dates. Only a few approaches emerged over the last years that focus on the operative phase and include forecasts in their planning. Very few contributions include port-side resources, like storage areas, loading bay availability, or heavy-duty handling equipment. Nevertheless, studies show ongoing trends to increasing numbers of installation, refurbishing or decommissioning projects with higher numbers of turbines [3], paired trends to larger and heavier turbines [22], which could quickly lead to bottle necks within the base port availability [12].

This article proposes a cascading simulation framework to support operations in determining suitable resupply cycles for components to adapt these cycles to the current, predicted needs at the base port. Therefore, the framework applies an online simulation as digital twin of the installation process. At each decision point, i.e., when the transport vessel starts a new resupply cycle, the digital twin evaluates some previously optimized alternatives given the current state of the installation and current forecasts as nested simulations. As the framework allows each of these child-simulation runs to apply the same decision process, it denotes each set of alternatives as a cascade. In general, the approach aims to reduce the required base port storage capacity and initial inventory level to reduce costs and save spaces for concurrent projects.

This article is an extended version of a contribution that was presented at the 2021 ASIM conference "Simulation in Produktion und Logistik" [15]. In extension, this article provides a detailed description of the framework, proposes a different method to select viable weather data for the nested child simulations, and extends the discussion of the approach's advantages and disadvantages by adding a second real-world use case, modeling the installation of the wind farm "Hohe See".

1 Methods for Offshore Wind Farm Installations

Compared to other areas in the offshore sector, only a few articles consider installing offshore wind farms [21]. Most articles deal with optimizing or evaluating the installation process [16], e.g., focusing on ways to simulate weather conditions [11], different installation concepts [21], or fleet mixes [1]. Other authors provide models to schedule the commissioning of vessels [8] or operations in various resolutions, e.g., [7, 20].

Even fewer articles explicitly include port-side resources like storage spaces or the resupply of components. For example, Beinke et al. (2017) [2] evaluated sharing heavy-lift vessels between several installation projects to reduce downtime due to bad weather conditions. Newer works demonstrate an increasing demand for jack-up vessels and, in consequence, port-side resources, as first wind farms reach the end of their life and require refurbishing or decommissioning [3]. Oelker et al. (2020) [12] evaluate available heavy-duty storage areas at the base port in Eemshaven using a simulation study. The study shows that the port's capacity will reach its limits soon if current trends continue. Rippel et al. (2020) [18] describe a mathematical model to determine optimal resupply cycles based on their efficiency that will be introduced later in this article.

In conclusion, the current state of the art mainly focuses on the actual installation and generally assumes that the base port offers sufficient components. Only a few of the presented models consider the resupply, but all assume a fixed and reliable resupply of components in defined intervals.

2 Process Description

Different installation concepts for offshore wind farms exist in the literature and practice, ranging from the so-called conventional concept, where all assemblies take place at the installation site, over preassembly concepts to floater concepts, where all assemblies take place in the base port. Practice and research mainly apply the conventional concept, depicted in figure 1. While this section shortly summarizes this concept, a more detailed description can, e.g., be found in [13, 21].

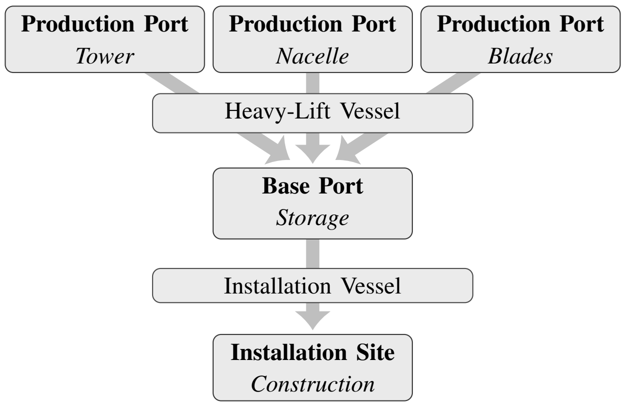

Figure 1: Conventional installation concept (c.f. [17]).

In this concept, a heavy-lift vessel travels between the components' production ports and the base port, which buffers the components for the installation. An installation / jack-up vessel loads sets of components and travels to the installation site to perform the assembly. Jack-up vessels possess retractable pillars to mount themselves at the installation site, effectively puncturing the sea bed to steady themselves against high waves. While this process allows mitigating the influence of higher waves, it results in the vessel's need to remain stationary until it finishes installing a turbine. Additional jack-up operations close to an already visited location can easily damage already installed foundations or even the vessel itself due to the already loosened sea bed. Consequently, installation vessels always need to load complete sets, i.e., all tower segments, the nacelle and hub, and all blades required for a turbine. Their capacity in terms of deck area and maximum payload restrict the number of sets. Most vessels currently available on the market can handle four sets.

Accordingly, installation operations require complete sets to be available at the base port to start, which, in turn, requires careful planning of the resupply of components. Therefore, practice and research assume that the heavy-lift vessel follows a predefined resupply cycle, visiting the production ports in a given sequence. At the end of each cycle, a defined number of complete sets become available at the base port. For example, such a cycle could consist of two trips: the first trip fetches two towers while the second trip visits the other two ports and fetches two nacelles and six blades. In this example, the first trip does not allow further installation operations as it is not possible to install only the towers. Nevertheless, after the second trip, two additional installation operations become available.

Generally, project planners decide on a single installation cycle during the planning stage of installation projects, which the heavy-lift vessel repeats until it finishes delivering all sets. On the one hand, this approach ensures the reliable delivery of components. On the other hand, this approach does not consider the current situation during the project execution. The actual demand varies depending on the current weather situation and forecasts. For example, fixed cycles can quickly deplete the storage when facing a good weather period. In contrast, bad weather periods heavily reduce the demand and can result in inventory overflows, requiring expensive additional storage areas or disrupting the supply chain. In practice, planners tend to include safety margins to the base port capacity and initial inventory levels to circumvent these problems.

Nevertheless, both examples can be faced by adjusting the resupply cycle according to the predicted demand. For example, longer cycles can bridge bad weather periods by slowing down the delivery. Accordingly, shorter cycles provide lower amounts faster to the base port to fully exploit good weather periods.

3 Demand-driven Resupply by Cascading Simulation and Optimization

This section introduces the cascading simulation framework used to select viable resupply cycles based on the current state of the installation process. The framework relies on a set of optimal resupply cycles that differ in duration and number of delivered sets but provide an optimal cycle considering the number of allowed roundtrips between one or more production ports and the base port. At each decision point, i.e., before a new cycle starts, the framework initializes several nested simulations, each evaluating the influence of an alternative cycle on the overall installation project using aggregates of historical weather records as depicted in figure 2. Please refer to, e.g., Kindler (2004) [9] for more information on nested simulation in general.

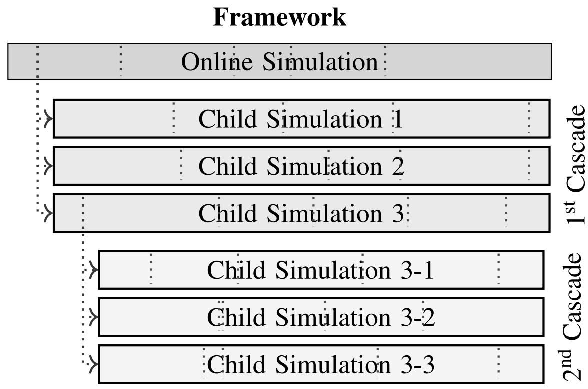

Figure 2: Schema of the cascading simulation concept using three alternatives and two cascades. Dotted lines represent decision points within each simulation.

This article uses the framework's digital twin (online simulation) to simulate installation projects using real-world scenarios and historical weather records to be as close to real-world applications as possible. Overall the framework consists of three major components: first, the optimization of resupply cycles, second the simulation model used for online and nested offline simulations; and third, a simulation manager to instantiate the nested child simulations and evaluate their results. While the optimization model supplies inputs to the framework, the later components, i.e., the simulation model(s) and the manager, interact directly during the simulation run as indicated in Figure 3.

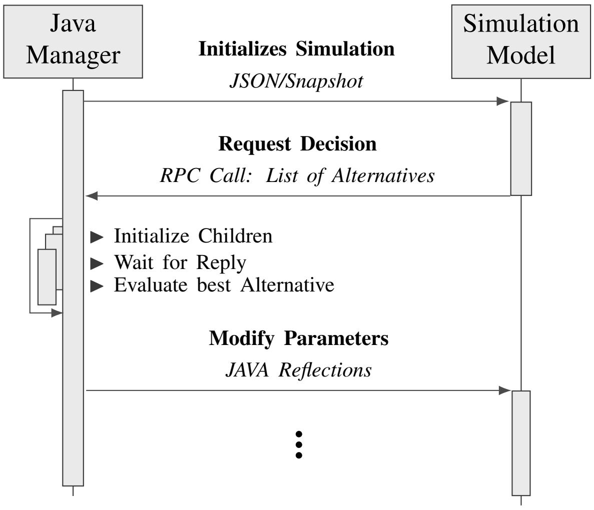

Figure 3: Interaction between the manager and the simulation components.

Once the manager starts, it initializes and runs its simulation model using a definition of the current state in a JSON file and, if it is a nested simulation, an additional copy of the parents state using AnyLogic's Snapshot feature. While both files contain partly redundant information, the JSON state contains additional information, e.g., which set of historical data a nested simulation should use or if the simulation could inquire the manager about decisions (given by the number of allowed cascades). Moreover, the manager registers itself within the simulation model as an external listener, allowing the simulation to call specified interfaces, e.g., when finishing or requesting a decision.

After initialization, the simulation model starts and proceeds until it reaches a decision point. It generates a list of alternative decisions, for example, by looking up already stored resupply cycles, pauses itself, and provides the alternatives to its manager by requesting a decision.

Upon receiving a request, the manager spawns additional instances of itself, providing one of the alternatives and a Snapshot of its simulation's state to each child manager. Each of these new managers then follows the same procedure. After concluding their simulation runs, the child managers report their results to their parent, which evaluates their results, and decides on the best alternative. Finally, it directly modifies its simulation using JAVA Reflections and instructs the model to resume simulation with the new settings. This process repeats for each decision point until the online simulation finishes.

The manager evaluates several characteristics of its child simulations' results to select the best alternative. First, it selects those alternatives that resulted in the shortest project duration as a prolonged time indicates missing inventory. Second, it selects those instances that would result in the lowest added storage capacity. If several instances remain, the manager selects the alternative cycle that delivers the most components as tie-breaker.

3.1 Optimization of Resupply Routes

The framework's primary objective in this article is selecting viable resupply cycles based on the current state of the installation process. This article defines a resupply cycle by the round-trips that the heavy-lift vessel takes, the number of delivered sets by the end of the cycle, and its duration. Thereby, the efficiency of a cycle depends on the number of allowed round-trips N, the geographical location of the ports, i.e., traveling times, and the vessel's capacity in terms of deck area and payload, i.e., the number of components that it can transport in one round-trip. Figure 4 shows the possible round-trips for the offshore domain when assuming symmetric traveling times.

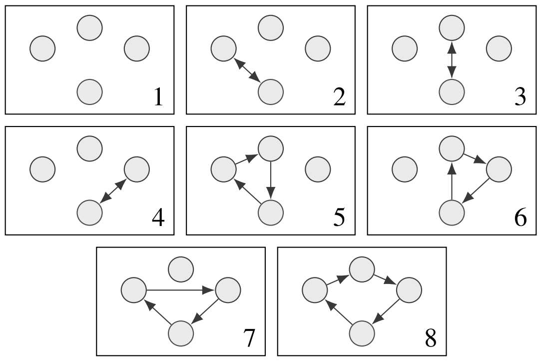

Figure 4: Possible round-trips for three production ports (top) and one base port (bottom).

It shows a total of eight possible round-trips when considering one base port and three production ports for the towers, blades, and nacelles. Consequently, the search space for creating a set of alternative resupply cycles that allow different numbers of round-trips is given as $\sum_{n=1}^{N} 8^n$. For example, assuming the framework wanted to evaluate the best alternative for allowing one to ten round-trips, the search space would already comprise 1.2 billion possible combinations. Assuming that evaluating a single alternative would take about one second, the sheer number of combinations would result in computational times of approximately 13.888 days. It has to be noted that this example only includes combinations of visited ports and completely neglects different loading scenarios at each port. In conclusion, the framework requires additional methods to reduce this search space.

Instead of applying meta-heuristics or other search-based techniques that still need to search large parts of the search space, the framework relies on mathematical optimization to generate optimal alternatives as soon as the supply network, i.e. the locations of the ports and the heavy-lift vessel are defined. The framework uses the model proposed in Rippel et al. (2020) [18] to derive a set of optimized alternatives for each allowed number of round-trips.

In general, the creation of a resupply cycle constitutes a combined routing (traveling-salesmen) and knapsack problem to determine (a) which ports to visit in each round-trip and (b) which components to load at each visited port. The problem aims to maximize the yield while minimizing the traveling-, loading-, and possibly setup times. The model exploits the small size of the transport network by enumerating possible routes for each round-trip (one to eight as shown in Figure 4)). It then calculates the traveling times for each of these routes using the well-established haversine formulae, solving a number of traveling salesman problems. The actual optimization model is then given as a customized multi-periodic knapsack formulation to maximize the number of delivered sets over N round-trips (periods). The model tracks visited ports in each round-trip as a binary vector, using a standard binary encoding to map these visits to the index of the precalculated traveling times. In addition, the model includes loading and unloading and setup times, e.g., for installing or removing transport frames on the heavy-lift vessel.

The framework applies this model to generate alternative cycles for one to N round-trips before the simulation run starts. While this offline optimization assumes that transport processes are mainly unaffected by weather conditions, planners could choose a safety margin to the expected cycle duration or even earlier, to the corresponding loading and unloading times. Nevertheless, most operations involved in the resupply show comparably high weather limits, which renders the assumption quite realistic. As a result of applying this offline optimization, the framework only evaluates N alternatives at each decision point instead of possibly millions of combinations.

3.2 Simulation Model

Both the online and nested child simulation runs use the same underlying model extended from Rippel et al. (2019) [19] but use different weather data. The online simulation uses actual, hourly weather records from the simulated period. Child simulations only have access to historical data, usually records of years prior to the simulation period.

The simulation model has been implemented in AnyLogic 8.7.9 professional. Figure 5 shows a screenshot of the simulation model. It contains agents for all vessels (installation and heavy-lift transport), the installation site, and the respective base and production ports. Therefore, ports and the installation site mainly manage their data, e.g., current storage levels or the number of installed turbines. In contrast, vessel agents can decide their following actions, e.g., creating and selecting installation cycles using weather forecasts. In the context of this article, the model has been modified for heavy-lift vessels. Heavy-lift vessels can access all predefined alternatives instead of only applying a single predefined resupply cycle. They can inquire the external framework which of these to choose for the next iteration. In general, the model contains various functions to estimate the duration of operations given a weather forecast and the operations' weather limits as proposed in the literature [17].

As noted, child simulations only access historical records as the framework cannot know how the weather will be in practical applications, even if this article only simulates historical projects. While the previous article proposed to use 20 years of historical weather data, i.e., mean values from 1979 to 1999 when simulating the year 2000 for the child simulations, this article proposes to search for similar years within the available data set to find better matches. The approach was modeled as a simplified version of known K-Nearest Neighbor Searches known in time series prediction (e.g., [10]). Therefore, the framework selects three months prior to the simulated project and calculates the duration of installation operations within this period. Afterward, it

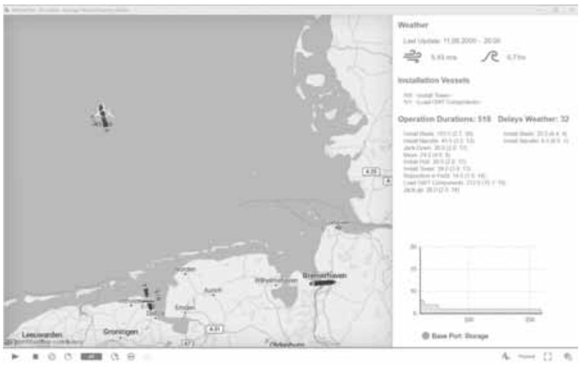

Figure 5: Simulation model implemented in AnyLogic 8.7.

iterates through the database, selecting each year Y^s in the database and a viable number of historical years $Y^N \in \{0,1,2,5,10,20\}$ and calculates the mean value and hourly standard deviation. The framework again estimates the duration of installation operations using the Markov-Chain-based approach described in [17] using these values as input. Finally, it calculates the Pearson-Correlation Coefficient between these sets and the last three months to decide for a constellation that matches the current data as good as possible. Earlier tests show that this approach represents the expected weather data better in most cases than just picking the last 20 years as originally proposed in [15]. In the following, the first use case still chooses to pick the last 20 years as these still show the highest correlation. In contrast, the second use case chooses a data set comprising five historical years from 1982 as the best match.

In addition to the aggregated historical data, parent simulations can provide actual weather forecasts to their nested child simulations, usually spanning a short period of 2-3 weeks. If provided, the simulation model interpolates between the forecast and its weather data using the expected uncertainty of the forecasts. This model uses data taken from the homepage of the German Weather Foundation [4], stating that the uncertainty of forecasts starts at 0.0 for the first hour (measurement), increases to approximately 0.25 at one week, 0.65 at two weeks, and rises to 0.95 at three weeks. Interpolating these values as $u(t)$ the model calculates the current weather conditions as function f over the time in hours t and the two vectors of weather conditions for historical data d_h and forecast data d_c: $f(t,\, d_c,\, d_h) = (1-u(t)) \cdot d_c + u(t) \cdot d_h$.

4 Experimental Setup

This article applies the cascading simulation framework to two different use cases. Both use cases model real-world installation projects in Germany's Northern Sea with different characteristics considering the projects' dimensions, supply network, and applied vessels.

Data for the first use case has been empirically collected during several research projects, resulting in in-depth knowledge, e.g., about processing times, weather restrictions, loading scenarios, resupply cycles, or installation vessels (IV). Beinke et al. (2017) [2] first published this use case. Accordingly, this experiment applies the same weather limits. Apart from these data, the use case relies on averaged characteristics for the heavy-lift transport vessels (HLV) in terms of their speed, deck area, and payload, as presented in the literature [18]. Comparing the results of the optimization model introduced earlier with the resupply cycles used in the real-world scenario shows a close to perfect match between the results. This match indicates that the vessel used had similar characteristics [18]. Table 1 summarizes the relevant parameters for this first use case.

Parameter	Tower	Blade	Nacelle
Project Start	April 1st 2000		
Base Port	Eemshaven		
Installation Site	Northern Sea		
Number of Turbines	50		
Number of IVs	1		
HLV: Deck Area / Payload	2646m^2 / 8900 t		
HLV: Avg. Speed	9.5 knots		
Production Port	Cuxhaven	Bremerhaven	Bremerhaven
Loading / Unloading / Setup Time	2 h / 1.2 h / 0 h	8 h /4.8 h / 0 h	10 h / 6 h / 0 h
Weight	600 t	240 t	500 t
Req. Space	650 m^2	300 m^2	263 m^2

Table 1: Parameters of the first use case.

The second use case represents the installation for the wind farm "Hohe See" in Germany's Northern Sea. The use case relies on publicly available data about used vessels, the supply network, or the wind farm location, e.g., [6]. While keeping the same weather limits, process durations, and heavy-lift vessel characteristics, this use case features a much larger supply network, more turbines to install, and a second installation vessel as shown in Table 2.

Parameter	Tower	Blade	Nacelle
Project Start	April 1st 2019		
Base Port	Esbjerg		
Installation Site	Wind Farm "Hohe See"		
Number of Turbines	71		
Number of IVs	Blue Tern, Brave Tern		
Production Port	Rotter-damm	Aalborg	Cux-haven

Table 2: Modified parameters of the second use case.

Both use cases use the same data set for weather data, containing hourly measurements from 1956 to 2019 within a few kilometers of both installation sites. As noted before, the nested child simulations use aggregated weather data for 1979-1999 (first use case) and 1977-1982 (second use case).

The simulation tracks the inventory levels of the online simulation to evaluate the efficiency of the cascading framework compared to an optimized fixed cycle. Accordingly, the first use case applies a cycle consisting of four round-trips that deliver eight sets in 312 hours. This cycle has also been applied in the real-world project and has been proven to be the most efficient cycle possible [18]. As the applied cycle is unknown for the second use case, the experiment first applied the described optimization to determine the most efficient cycle. In this use case, again, a resupply cycle using four round-trips, delivering eight sets over 408 hours, provides the lowest time per set.

The experiment assumes an infinite storage capacity but tracks how much inventory was used during the simulation to determine the required capacity. The experiment varies the initial inventory level between 0 and 20 in steps of two for the first use case and between 0 and 50 in steps of 5 for the second use case to determine the lowest possible initial inventory for the fixed cycle and cascading framework. Finally, it tracks the actual inventory levels throughout the simulation to enable comparisons in the behavior of both approaches.

5 Results and Discussion

Figure 6 shows the results for the first use case. The top graph shows the project duration for different initial inventory levels. The results show that the cascading concept achieves an uninterrupted installation process starting at an initial inventory level of ten sets. In contrast, the fixed cycle requires at least twelve sets to avoid delays due to missing inventory. The graph in the middle shows the observed maximum inventory. Both approaches require a capacity equal to this level, starting from an initial inventory of eight sets. Finally, the lowest graph shows the current inventory level over time. The graph shows no relevant differences, resulting in similar average inventory levels.

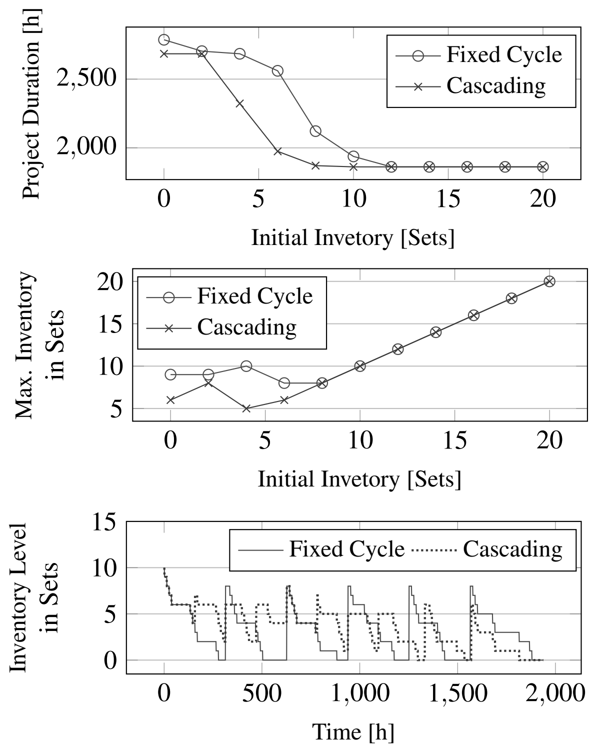

Figure 6: Results of the first use case.

Figure 7 shows the same graphs for the second use case. Considering the project duration, the second use case shows the same characteristic as the first use case: the cascading approach achieves an uninterrupted installation at an initial inventory level of 30 sets instead of 35 sets for the fixed cycle. Similarly, both approaches' required capacity is equal (second graph). In contrast to the first use case, the last graph shows interesting behavior. The cascading approach quickly reduces the initial inventory level, maintaining a lower average inventory level until the end of the project.

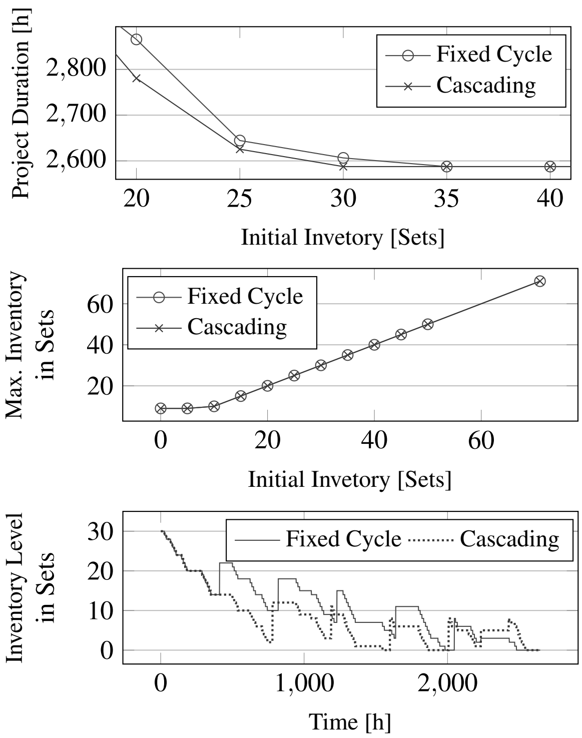

Figure 7: Results of the second use case.

6 Conclusion and Future Work

This article presents a framework to combine cascading simulation with offline mathematical optimization to choose viable resupply cycles for offshore installation projects based on the current state of the process, weather forecasts, and expected weather conditions. Compared to purely heuristic or search-based approaches, this combination limits the search space drastically, rendering it a viable alternative in practical applications. The same accounts for purely mathematical approaches. Combining the scheduling of vessels with the routing and knapsack problems involved with the resupply would probably result in a problem with vast amounts of constraints, probably unsolvable in a realistic context.

The results show that the approach reduces the required initial inventory level compared to optimized fixed resupply cycles. As the required capacity increases linearly with the initial level, the framework can provide a tool to reduce the strain on port-side resources. Moreover, the second use case shows that the framework can, in some cases, result in a heavy reduction of the average inventory level at the beginning of a project. This behavior can be exploited to free up reserved capacity. The advantage of the cascading concept also shows in its transparency. At each decision point, the framework offers its current decision. In the second use case, the framework decides for a long resupply cycle initially, resulting in the drop of the average inventory level. Moreover, planners could also evaluate the respective nested child simulation to predict the remaining project's behavior.

Future work will further investigate this effect and determine which constellations result in such behavior. Moreover, future work will investigate other applications for the cascading framework in the offshore area and other simulation-based optimizations. The current implementation allows easy integration of the cascading framework to various models implemented in AnyLogic by providing suitable interfaces to register the manager class and the means to provide it with decision alternatives.

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A Simulation Study on Electric Last Mile Delivery with Mobile Smart Cargo Boxes

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Abstract. The increasing popularity of e-commerce requires efficient solutions for the provision of last mile logistics. There are different approaches for delivering parcels, e.g., home delivery, service points, or parcel lockers, which have different advantages and disadvantages for customers and logistics providers in terms of flexibility, accessibility, and operating costs. We have studied a novel transportation solution where electric vehicles dynamically set up smart cargo boxes, from which customers can fetch their delivery at any time of the day. This provides customers with a more flexible access to their packages and allows the service provider to deliver the parcels more efficiently. In this article, we present the results of a feasibility study conducted in Västra Hamnen, Malmö (Sweden). The developed simulation model shows that smart boxes not only are a viable approach for efficient last mile deliveries, but also result in considerably smaller travel distances compared to conventional package delivery system.

Introduction

Even before the beginning of the Covid-19 pandemic, business to consumer (B2C) e-commerce has experienced a steady growth. However, due to interventions for containing the pandemic such as movement restrictions and lockdowns as well as recommendations against visiting physical stores or even their closure, the importance and popularity of online shopping increased further (Elrhim & Elsayed 2020). A major challenge that arises from the growing trend towards online shopping is the effective realization of B2C last mile delivery, i.e., the delivery of the parcel from a regional depot to the customer (Mangiaracina et al. 2019).

There exists a great number of logistics service providers that pursue different last mile delivery approaches. Common last-mile solutions for B2C are to deliver the parcel to (i) the home address, (ii) service points where they are picked up by the customers, or (iii) stationary parcel lockers that are located at supermarkets or other frequented places, where customers can pick up their parcels. As outlined by Allen et al. (2007), these delivery alternatives provide customers but also service providers with different advantages and disadvantages regarding flexibility, accessibility, and effort of the pick-up process. Customers, for instance, experience shorter retrieval times and are not limited to opening hours when using parcel lockers compared to service point deliveries. However, compared to attended home deliveries, parcel lockers and service points do not require the customer to be present upon delivery and, thus, increase the customers' flexibility in terms of the delivery time window. Yet, pick-up points are limited in their opening hours and require each customer to travel there, which they might consider to be inconvenient.

From a logistics provider's perspective, these delivery options vary in efficiency. Compared to pick-up service points, home delivery results in increased delivery costs, a higher number of failed deliveries, and a significantly greater driving distance for delivery vehicles, which also might affect traffic congestion and exhaust emissions. Moreover, the delivery option with parcel lockers is more time-consuming for the driver as he or she needs to fill the lockers with new deliveries. For both parcel lockers and service point deliveries, it can be assumed that the cumulated customer travel distance is significantly higher in relation to the travel distance of the service provider. It is challenging to take all these, potentially conflicting, requirements into account and to find a balance between the requirements of the customer and logistics providers.

To address this issue, the Swedish start-up DiPP-R (www.dipp-r.com) develops a transportation solution to improve the efficiency of last mile delivery of e-commerce parcels. The idea is that electric vehicles dynamically set up smart cargo boxes at different locations in the city. These boxes can hold between 50 and 100 packages and are dynamically placed at, for instance, parking areas. This enables the customers to pick-up their deliveries at any time during the day. After all parcels were picked up by the customers or after a certain time, the boxes are collected by the vehicles, refilled at the depot, and placed at other locations. The aim is to reduce the handling of parcels outside the depot and to decrease the distance recipients must travel to fetch their parcels. This results in increased convenience and shorter total travel distance, ultimately reducing traffic congestion and environmental impact.

This article presents the results of a feasibility study that was conducted by Malmö University, the city of Malmö, and DiPP-R. As part of this study, a simulation model was developed to investigate the effects of this new delivery concept and how it can be realized. The simulation model allows for analysing the efficiency of different service designs in Västra Hamnen, a district in northern Malmö (Sweden). The simulation model also enables the comparison of this new approach with traditional delivery concepts, such as home delivery and central service points.

In summary, the simulation model can be used to answer research questions such as

- How does the new concept perform compared to existing delivery services in terms of, for instance, travelled distance, accessibility for customers, environmental and traffic impact?
- How shall smart cargo boxes be configured and how many compartments are required per box?
- How many setup locations are required to efficiently serve a particular area and where should they be located?
- Which pick-up and drop-off strategy is most efficient in terms of travel distance?
- How do variations in demand affect the service quality?

The paper is structured as follows: In Section 1, we provide a description of related work on last mile logistics and its simulation. We then describe the simulation model we developed, followed by a specification of the experiments and the results. After a discussion of the results, we provide conclusions and discuss future work.

1 State-of-the-Art

The use of simulation for analysing and comparing logistics processes is well established and studied (Manuj 2009). In transportation logistics, simulation is used to analyse, for instance, how transport tasks can be allocated to vehicles (Davidsson et al. 2005). According to Olsson et al. (2019), modelling and simulation is the leading methodology used in the emerging research area of last mile logistics. It is applied to investigate, e.g., the effects of different means of delivery such as electric vehicles and cargo-bikes but also the feasibility of crowdsourcing. This is, as simulation allows for creating digital copies (*digital twins*) of real-world systems, that can be used to efficiently investigate the system's behaviour under different circumstances, without influencing or jeopardizing the real-world system.

Grando & Gosso (2005) refer to the issue of identifying the optimal delivery solution as "*Last Mile Logistics Dilemma*" and present a reference model for comparing home delivery with pick-up points. To overcome this dilemma, Perboli et al. (2018) propose a multimodal simulation optimization framework for urban freight transportation of e-commerce deliveries, which allows for analysing different delivery modes in realistic scenarios. Besides such frameworks, there exists other studies for specific scenarios in last mile logistics. This includes, for instance, the use of robots for autonomous last mile deliveries, e.g., (Poeting et al. 2019), or for crowdsourced delivery, e.g., (Guo et al. 2019), where local non-professional couriers deliver the parcels to the customers' homes.

The use of cargo boxes has been mostly studied for scenarios with stationary boxes that are equipped to the customer's house or set up at fixes publicly accessible locations. To optimize the last mile in electronic grocery shopping, Punakivi et al. (2001) simulate the use of delivery and reception boxes for unattended delivery of groceries. Yetis & Karakose (2018) propose the use of smart cargo cabinets that are located within buildings and fed by unmanned aerial vehicles (drones). For a Polish city, a study has been conducted by Iwan et al. (2016). The results show that a reduction of the environmental impact of last mile delivery can only be achieved by alternative delivery concepts such as parcel lockers. A similar study has also been conducted in the Netherlands, which investigated the potential of cost reductions when shifting from home delivery to parcel lockers (Van Duin et al. 2020).

To our knowledge, there exists no simulation studies on smart cargo boxes that are dynamically placed at different locations in the city with the aim of optimizing delivery processes for both customers and logistic service provides.

2 Modelling Last Mile Delivery Options

We implemented an agent-based model (ABM) to investigate the effects of different last mile delivery options. The delivery vehicle, customers, deliveries, smart cargo boxes, potential locations of the boxes, and the depot are implemented as agents. Each day, a number of deliveries arrives to the depot each of which is designated for a specific customer in the simulated area. According to the customers' home addresses, the deliveries will be allocated to boxes such that the customers' travel distance for picking up their parcels is minimized. This includes the clustering of the deliveries for the allocation to the boxes as well as the identification of optimal setup locations for each box. A vehicle will then transport the boxes, one at a time, to their designated location. In case there is already a box standing at this location whose minimum setup time (e.g., after 24 hours) has been reached, it will be replaced, and the previous box is returned to the depot. Packages remaining in the returned box will then be allocated to new boxes in the same manner as newly arrived packages. The vehicle visits the box locations in an order prioritizing empty boxes and those that have exceeded their minimal setup time. Boxes that are placed at a location may not be completely filled with packages, however, the vehicle will never deliver empty boxes and will skip locations to which no packages are to be delivered. During hours with high volume of traffic (e.g., 6 a.m. – 9 a.m. and 3 p.m. – 6 p.m.) the vehicle will not leave the depot to reduce traffic congestion.

Each customer has a home address, from where he or she will pick up the parcel. Once a box with a parcel arrives at a pick-up location, there will be a random delay representing that the customers are occupied with other activities and that they pick up their deliveries at a later point in time. If the box with the package has not been returned to the depot by then, the customer walks to the location of the box, takes its package and walks back home. Otherwise, the customer will be informed when the delivery can be collected from another box.

In case the distance to the box is greater than a given threshold, the recipient will choose to take the car instead of walking.

Modelling of customer demand is challenging and requires data on where customers live as well as on their habits. For this study, each customer and delivery need to be assigned to a specific building to adequately simulate driving and walking distances to distribute and pick up parcels. Hence, address data is needed on where people live. This data is usually not openly available such that other data sources must be used to generate realistic artificial data on customer demand. OpenStreetMap (OSM; openstreetmap.org) data, for instance, can be used to geographically distribute customers in a realistic way. From OSM, positions of buildings can be extracted as well as their size and utilization. This allows us to identify the potential home addresses of customers and to estimate the likely number of residents. We do this by distributing the known number of inhabitants of the simulated area to the buildings we identified in OSM. Here, we use the floor area of the houses to estimate the number of residents by calculating the average floor area per resident. Due to a lack of data, the modelled population is homogenous in terms of their behaviour and habits, e.g., the threshold when they will use a car to fetch their delivery.

The model allows for comparing the new delivery concept to two traditional package delivery systems: deliveries to service points and home deliveries. For service point deliveries, different pick-up locations are defined, where the service points are located. Each time a customer fetches a package from a box, the walking distance from their home to one of the delivery locations and back is simulated as well. For home delivery, every time new packages are delivered to the depot, a route is iteratively planned such that packages are delivered to the recipient closest to the last one. This does not return the minimum distance required to deliver all packages but overestimates the delivery distance. Yet, we do not consider extra driving distances potentially caused by time windows for home delivery. Moreover, we assume that only one vehicle is in charge of all home deliveries.

For analysing different scenarios, the model provides the following parameters:

- The **number of packages delivered to the depot** each day. Each arriving package has an individual defined as its recipient.
- The **minimum set-up time of boxes** to stay at a location before it can be picked up or replaced by the vehicle.

- The **package capacity of the boxes**. Packages that do not fit in a box will be delivered with the next box to the same location or a suitable location close by.
- The **rate at which customers collect their packages** as the lambda parameter of the exponential function for determining waiting times of customers.
- The **maximum walking distance of recipients** before taking the car for fetching a delivery. We assume all individuals have access to a car.
- The **ratio of individuals fetching their packages combined with other activities.** If individuals fetch their package together with other activities, e.g., buying groceries, only the additional distance needed to fetch the package is considered. The customer will move from its home to the grocery store, to the box, and back home. In case the grocery store contains a delivery point, the additional distance is zero

The following outputs are provided for each run of the simulation model:

- The **total distance the delivery vehicle has travelled**.
- The **total time the vehicle is being active**.
- The **total distance of customers** to pick up their packages and to return home.
- The **distance of customers travelled by car** in case the distance to the box is above the car threshold. Driving distance can be longar than walking distance.
- The **number of deliveries that have been picked up** by the recipients.
- The **number of packages that have not been picked up by the customers** and thus were returned to the depot for a new delivery with another box.
- For *service point deliveries*:
  - The **total distance of customers** to fetch their packages and return home.
  - The **total distance of customers travelled by car**.
- For *home delivery*:
  - The **approximated total distance** travelled by the home delivery vehicle.
  - The **approximated total time** all deliveries will take.

3 Case Study: Smart Cargo Boxes in Västra Hamnen

The model was implemented using the AnyLogic simulation framework (www.anylogic.com). For this feasibility study, we have chosen the neighbourhood of Västra Hamnen in Malmö (Sweden) as the setting for our experiments. The potential locations of the boxes as well as for the depot can be chosen manually.

To generate more realistic results, we have chosen the location of the depot to be close to the depots of other existing logistics providers and identified suitable locations, e.g., parking areas, for setting up the boxes. For the simulation of both service point deliveries and grocery stores, two existing service point locations were chosen. AnyLogic includes built-in geographic information system (GIS) support with real-world road networks, which is used to create routings for vehicles and individuals. The user interface of the simulation is shown in Figure 1.

For the generation of customer address data and customer demand, we have used OSM data of Västra Hamnen in Malmö. According to the data, there are 298 buildings in this area. Buildings with a floor area over 2.000 m^2 were assumed to be industrials buildings and not considered as residence of customers. Buildings between 200 and 2.000 m^2 are assumed to be apartment buildings and below 200 m^2 as single-family house. In total, Västra Hamnen has 9 739 inhabitants, which were distributed to the existing buildings according to their floor area, resulting in 9 155 customers living in apartment buildings and 584 living in single-family houses. Each of the 9 739 customers was assigned an address according to this distribution.

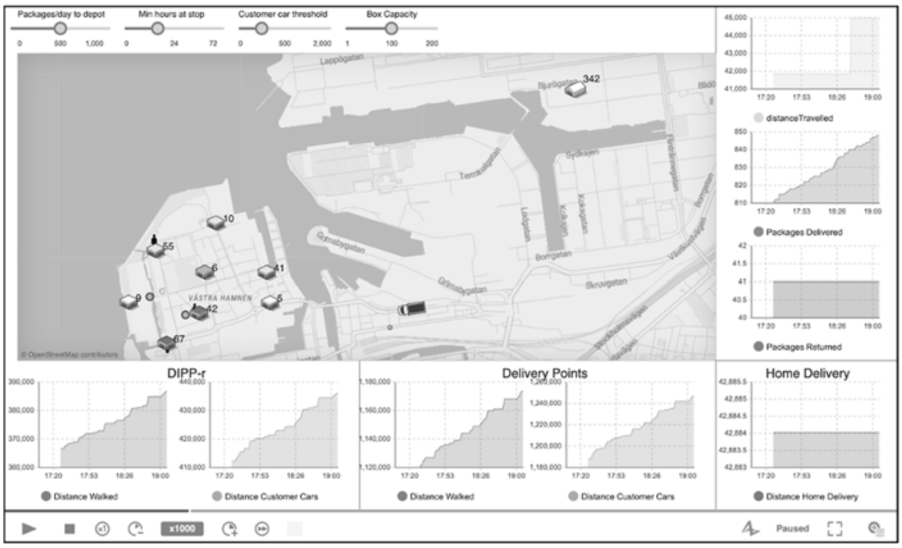

Figure 1: The user interface of the simulation model in AnyLogic.

4 Results of the Simulation Study

For the study, the simulation model was run using different combinations of input parameter values. The simulation starts at 8 a.m. and we simulate an entire week. The presented results were generated using 8 box locations, 9739 customers, and a single distribution vehicle. With respect to the comparability of the results, all simulations used a fixed random seed.

Figure 3 shows the distance travelled by vehicles for different delivery options and scenarios, i.e., thresholds when customers use their car to get their packages as well as packages per day. When customers chose not to use their car for picking up parcels if the distance is less than 1 km, the mobile smart boxes system results in considerably shorter driving distances compared to the delivery point system. Also, the distance is similar to the distance the home delivery vehicle has to drive, assuming it has a capacity of 100 parcels.

For the effectiveness of the service, it is not only relevant how many boxes are used but also where they are located. The placement of boxes and its effects on the distance customers must walk can also be explored using the model. For instance, in the two set-ups shown in Figure 2, the cumulated walking distance differs by 3.4%. Hence, the model can be used by decision makers to identify most suitable locations

The model also allows for varying the number of boxes and to investigate the effect this has on the service provision. We simulated the parallel set-up of 4, 6, 8, and 10 boxes with the locations of the boxes being determined using k-means clustering (see Figure 4). The results show a decreasing customers' travel distance and an increasing distance driven by the delivery vehicle, when the number of parallelly used cargo boxes increases. As shown in Table 1, increasing the number of boxes from 4 to 6 results in a 13.9% decrease of the customers' walking distance and 23.2% decrease of the distance driven by car (in total -18.8%) whereas the travel distance of the delivery vehicle increases by 48.8%.

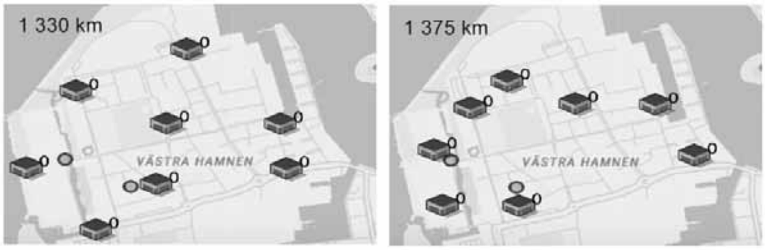

Figure 2: Total customers' walking distance for two different placements of boxes.

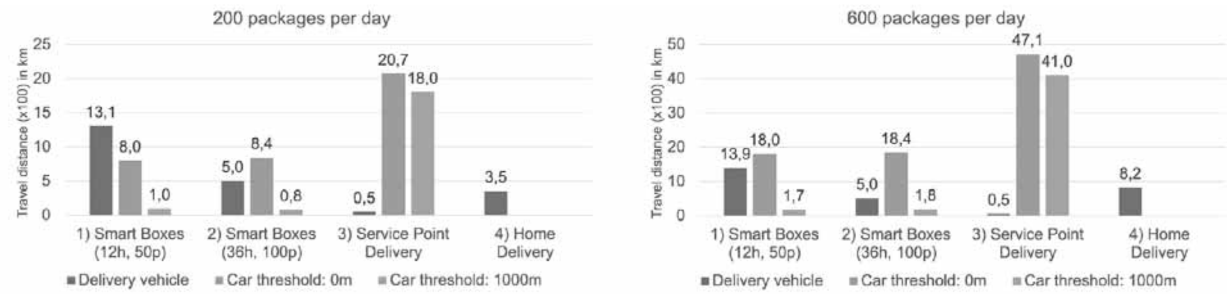

Figure 3: The distance (in km) travelled by the delivery vehicle and by customers using cars at thresholds of 0km and 1km for four scenarios: 1) Boxes, with a capacity of 50 packages waiting for 12 hours at stops; 2) Boxes, with a capacity of 100 packages waiting for 36 hours at stops; 3) Service point delivery; 4) Home delivery. The depot received 200 resp. 600 packages per day.

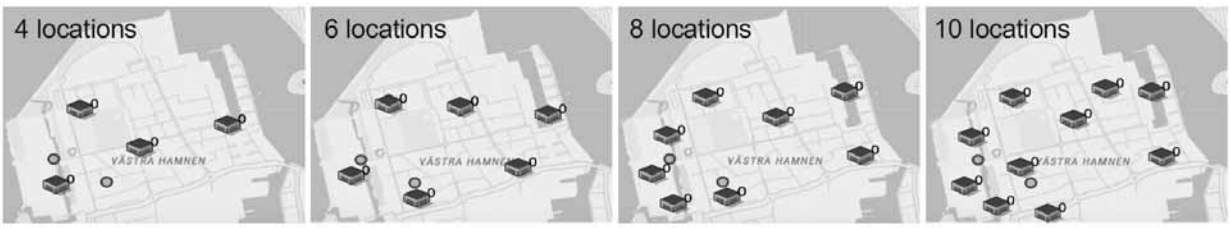

Figure 4: Different number and placement of set-up locations for smart boxes.

Number of cargo boxes	Distance walked by customers (km)	Distance driven by customers (km)	Distance delivery vehicle (km)
4	1717	1974	180
6	1478	1516	268
8	1453	1319	345
10	1346	1083	451

Table 1: Traveling distance of customers and delivery vehicle for different number of stops assuming that customers will walk in case the distance is less than 1km.

When increasing the number of boxes from 6 to 8, the total decrease in customers' travel distance is only 7.5% whereas the distance of the delivery vehicle almost doubles (+91.7%)

It can be assumed that some customers will combine the collection of their delivery with other activities such as grocery shopping, as service points often are located at grocery stores.

Figure 5 shows how the percent of individuals fetching their package combined with another activity affects the additional distance travelled by private car for both mobile smart boxes and delivery points. More people combining fetching their package with grocery shopping leads to smaller additional distances travelled. More interestingly, the smart boxes system is shown to lead to smaller distances travelled than the delivery point system for almost all scenarios.

An estimate of the cumulative time it takes to distribute the mobile smart boxes and to make all home deliveries is shown in Figure 6. For home delivery, each delivery is assumed to take one minute per address, the vehicle's movement speed is 15 km/h, and the capacity is 100 parcels.

The figure shows that the time the smart box delivery vehicle is active correlates with the frequency at which boxes are delivered and returned to the depot. Yet, it is largely unaffected by the number of packages being delivered. This is not true for the home delivery vehicle.

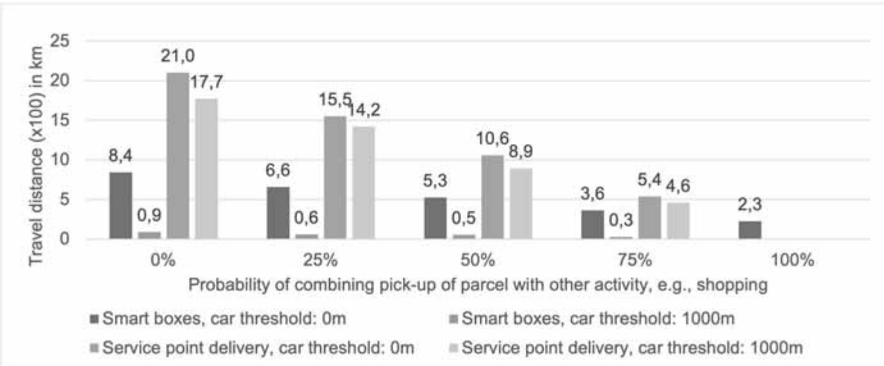

Figure 5: The distance (in km) travelled by customers by private car for different probability of combining the fetching of parcels with other trips, e.g., shopping.

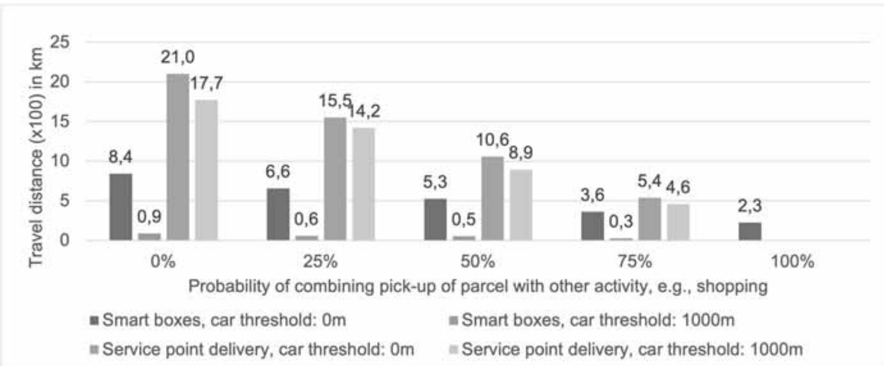

Figure 6: The cumulative time the delivery takes for smart boxes with a capacity of 50 packages being replaced after 12 hours, smart boxes with a capacity of 100 packages being replaced after 36 hours, and home delivery.

5 Conclusions

In this article, we have presented an agent-based simulation model for comparing a delivery solution with mobile smart cargo boxes to existing systems for last-mile delivery. The simulation explores the effects of different smart box service designs and results show that smart boxes are not only feasible as a delivery solution, but significantly decrease the distance customers must travel to fetch their packages and the total distance driven by vehicles compared to service point deliveries. For a car threshold of 1 km, the total vehicle distance is similar to the one of home delivery.

Yet, existing delivery systems have limitations that have not been included in this study. For instance, home delivery might require the recipient to be at home and service points usually have opening hours. With smart boxes solution, however, customers can fetch their packages whenever they desire during the day, allowing for increased flexibility. Moreover, the service provider can set up and collect boxes all day through, which increases the utilization of the vehicles.

There is a trade-off concerning the time boxes stay out before being returned to the depot. A shorter setup time reduces the time packages stay at the depot before being distributed. Recipients, however, have a smaller time window for fetching their packages. This, as well as the fact that not all individuals fetch their packages right away, increases the load at the depot and requires the use of more boxes. Also, reducing the time packages are available for pickup is less convenient to customers.

Examples of simplifications made in the model are the homogeneity of individuals and their habits, the assumption of a static threshold for fetching a parcel by car, and the exclusion of workplaces and other venues than grocery stores and service points. There is also no consideration of exhaust emissions of vehicles, which might be relevant for cities with low-emission zones. Another assumption is that only one delivery vehicle is used for all home deliveries. An extension of the model requires, e.g., data on the capacity of home delivery vehicles and the time to deliver packages

Besides the design of the service, local regulations and policies might affect the feasibility and viability of deliveries using mobile smart cargo boxes. This includes, for instance, parking regulations that might limit potential locations for setting up boxes and how long they can stand at a location.

Moreover, it is uncertain how different configurations of the service, e.g., the minimum setup time, affect customer acceptance and satisfaction. Yet, the proposed simulation model can be used to investigate different scenarios and to identify potential challenges and opportunities.

With respect to future trends, it is planned to use electric vehicles for the distribution of the boxes. To this end, the effect the battery capacity of the vehicles has on the service needs to be investigated as well as the approaches for charging the vehicles. It can also be assumed that many customers will combine the pick-up of their parcels with, for instance, their work trip. This might affect the optimal placement of the boxes as the location closest to the home might not be most convenient.

Acknowledgement

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Using Decision Trees and Reinforcement Learning for the Dynamic Adjustment of Composite Sequencing Rules in a Flexible Manufacturing System

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Abstract. Integrating machine learning methods into the scheduling process to adjust priority rules dynamically can improve the performance of manufacturing systems. In this paper, three methods for adjusting the k-values of the ATCS sequencing rule are analyzed: neural networks, decision trees and reinforcement learning. They are evaluated in a static and a dynamic scenario. The required dataset was synthetically generated using a discrete event simulation of a flow shop environment, where product mix and system utilization were varied systematically. Across all scenarios, it is shown that all three methods can improve the performance. On par, RL and NN can reduce the mean tardiness by up to 15% and compensate for unplanned product mix changes.

Introduction

Finding a good sequence of operations on a machine can be difficult under changing conditions, such as machine failure. Since the use of centralized and static solution methods is not suitable in complex and uncertain scenarios, decentralized sequencing rules are a viable option. These rules use locally available information for fast decision making. However, no rule exists that outperforms all others under varying system performance.

For this reason, a hyperheuristic is developed to dynamically select and adjust weighting values of a composite sequencing rule, selecting the next job to be processed based on the system state. Based on a variety of training scenarios considering several dynamic influences, such as stochastically distributed arrival times or changing proportions of product families in the product mix, the benefits of dynamically adjusting the k-factors of the rule is presented.

To estimate the performance of the system based on the current state, different machine learning models have provided very good results depending on the selection of the weights of the composite rule (Heger 2014; Mouelhi-Chibani and Pierreval 2010; Shiue et al. 2018). When using these methods, however, there is not only the question of the amount of training points, but also the aspect of transferability of the acquired knowledge in new scenarios and the suitability, generalizability and traceability of the methods used (Priore et al. 2006; Priore et al. 2018; Usuga Cadavid et al. 2020).

The knowledge and understanding of actions and decisions taken during the process is crucial and is increasingly preferred as opposed to simple prediction and black box optimization (Nunes and Jannach 2017; Rehse et al. 2019). At this point, the usage of hyperheuristics for the selection and adjustment of different sequencing rules in combination with comprehensible learning methods (e.g. decision trees) can prove useful. This contribution elaborates on the usage of three different methods to dynamically adjust the behavior with regards to performance and comprehensibility.

1 State-of-the-Art

Due to their ease of comprehension and very short computation time, the use of priority rules for sequencing, i.e. selecting the next job to be processed by the machines, is very popular in the industry. It should be noted that more than 100 rules are known, which perform differently depending on the scenario (Panwalkar and Iskander 1977). Over the years, priority rules which look at multiple job attributes simultaneously have been developed to improve system performance.

For example, the „Apparent Tardiness Cost“ rule, which, in addition to the weighted process time, also includes the planned completion time and a weighting value (k_1) (Vepsalainen and Morton 1987). With regard to setup times, the rule was then extended to include a setup time term and has been since described as "Apparent Tardiness Cost with Setups" (ATCS). The additional term denotes the ratio between sequence-dependent setup time and average setup time multiplied by the second weighting value (k_2). The rule is used in the form shown in equation (1) for this study. The combination of three attributes and the use of two weighting values make it possible to achieve good performance across a wide range of scenarios when properly tuned (Lee et al. 2002).

$$Z_i^t = \frac{w_i}{p_i} exp\left(-\frac{(d_i - t - p_i)^+}{k_1\overline{p}}\right) exp\left(-\frac{s_{i,l}}{k_2\overline{s}}\right) \quad (1)$$

Knowing that the system performance strongly depends on the correct selection of the k-values to match the system workload, they are required to be dynamically adjusted to the situation on the shop floor. Consequently, the dynamic adaptation is a hyperheuristic. However, to build the knowledge base about the relationship between the k-values and the resulting performance, all possible combinations of k-values, product mix and system state would have to be known.

Because of the complexity in real systems, not all possible combinations of influencing factors can be simulated. For that reason, a defined combinations of system states is simulated and the unknown situations are estimated by a regression procedure

In the current state of the literature, the use of neural networks (NN) represents the standard to forecast system behavior. Specifically, the usage of NN for the prediction of system performance was considered in detail with regard to the dependence on the k-values and the system status in multiples works (Heger 2014; Heger et al. 2016; Mönch et al. 2006; Mouelhi-Chibani and Pierreval 2010). However, despite good results, it should be noted that NNs are basically used as a black box and do not allow us to infer any information about the influence of certain factors. To this end, the use of NNs as a baseline was previously compared with the use of decision trees and reinforcement learning (Rai, 2020).

Decision trees have recently received significant attention in the context of Explainable AI (Puiutta and Veith 2020; Rai 2020).

Unlike complex methods, such as deep NNs, which produce non-interpretable black-box models, decision trees are rule-based methods that provide the user with an intuitive representation of rules and processes. At each node of a decision tree, a particular objective function is tested. The result provides the path to the new node. The structure repeats until a particular condition is met. Human comprehensible rules can be derived from paths through the decision tree.

Due to their structure, decision trees can be used for both classification and regression tasks. Thus, being generally suitable for dynamic selection of priority rules, they are prone to perform worse in unknown scenarios (Shahzad and Mebarki 2016). Other tree-based methods, such as Random Forest and XGBoost, based on a combination of decision trees and have forfeited a certain degree of interpretability in order to achieve better accuracy and generalization. Nevertheless, they are increasingly equipped with further functionalities to improve interpretability (Lundberg et al. 2020)

The use of reinforcement learning has already achieved good results as a hyperheuristic in the dynamic selection of sequencing rules. Studies show that the inherent advantages of reinforcement learning, as opposed to supervised learning methods, are in the direct interaction with the system. The agent learns the correct behaviors based on the observed behavior and the feedback received. Specifically, the use case entailing the selection of priority rules for all machines in the system (Heger and Voss 2020, 2021) has shown good results. The authors show that based on the observed system workload and queues, performance can be improved by dynamically selecting sequencing rules. Similarly, other authors show that dynamic adaptation of machine-specific rules enables significant performance improvements across different scenarios (Shiue et al. 2018, 2020).

This paper examines the extent to which the three aforementioned methods can be useful in supporting the selection of appropriate k-values for the ATCS sequencing rule. Specifically, the extent to which the use of comprehensible actions leads to a reduction in performance is to be examined. The interaction effects between performance and explainability is examined in more detail in the context of the presented scenario. In addition, using the trained hyperheuristics, it is to be tested whether they are still able to select and dynamically adjust the k-values according to the system state in an unknown scenario, thereby achieving a more robust performance

.

2 Simulation and Scenario

The study is used and conducted in the context of a manufacturing system with sequence-dependent setup times. Unplanned and unknown changes, such as product mix changes and workload fluctuations, are added to be able to look at a behavior of the different methods in unknown scenarios. The scenario is described in detail below:

System	Machines: 10 Machine Groups: 5 Structure: Flow shop
Job Parameter	Product types: 4 Distribution of product types: based on Product Mix Operations per Order: 10 Distribution of Interarrival Times: Poisson Process times: 1 – 99 Distribution of Process times: uniform Due Date: TWK Method
Simulation	Warm Up: 2500 Jobs Duration of Simulation: 12500 Jobs
KPIs	Average Mean Tardiness

Table 1: Detailed description of the flow shop scenario.

The particular focus in this contribution is to consider the impact of the sequence-dependent setup times, which are shown below. Depending on the product mix, the proportions of the four product types are different, which leads to different ratios of setup time. Thus, it can be assumed that a product mix with the first three product families requires significantly less setup time than a product mix containing all four product families. Here, the matrix in (2) can be read as follows: the setup time from family 1 to family 2 is 5 minutes; the setup time from family 1 to family 4 is 25 minutes. With an average processing time of 50 minutes, the setup time ratio can have a massive impact on the performance of the system.

$$\begin{pmatrix} 0 & 5 & 10 & 25 \\ 5 & 0 & 10 & 25 \\ 5 & 5 & 0 & 25 \\ 5 & 5 & 10 & 0 \end{pmatrix} \tag{2}$$

To measure performance, the average mean tardiness and the average lead time are documented. The average tardiness results from the sum of all deviations of planned completion time and the actual completion divided by the number of observations.

It should be noted that orders completed too early are assessed with a delay of zero. The due date, considered as the planned completion time, is calculated from the sum of the start time and the average planned processing time for all steps multiplied by a due date factor. The due date factor is selected so that a certain setup-, maintenance- and transport-time between machines is acceptable.

For the creation of regression models, training data is generated in an extensive parameter study using the discrete-event simulation model. The use of the simulation makes it possible to determine the length and width of the data set itself. The generated data forms the basis for the knowledge-based approaches to dynamic adjustment described later. In this case, the simulation model is available as a training environment for reinforcement learning as well.

Figure 1 describes the multiple steps of the procedure; starting at the bottom center is the simulation model. Through the parameter variation experiment it is possible to examine the behavior of the performance depending on different system state combinations, thus making it possible to create training data for the different regression models.

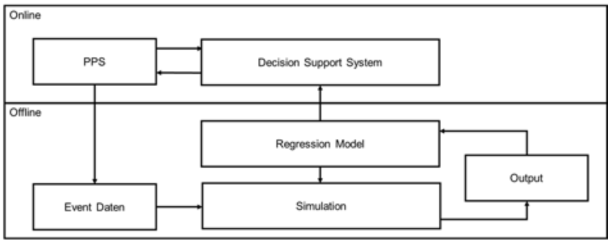

Figure 2: The regression model is trained offline based on the simulation and utilized online after training as a decision support system.

Figure 2 shows a schematic of the dynamic adaptation procedure during the online application. It considers the performance of the system over time and under changing states as well as the last selection of k-values. Depending on the selected performance indicator, the goal is to minimize or maximize this performance value; in this contribution, the minimization of the average tardiness is considered.

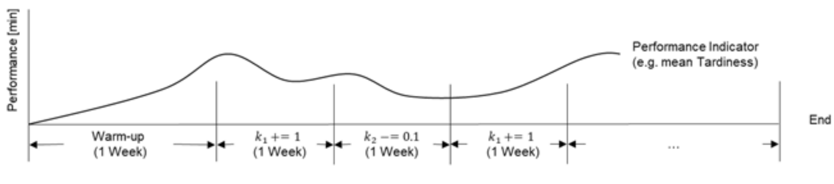

Figure 1: Generalized behavior of the adjustment of k-value pairs with RL.

At defined points in time, regardless of the particular method being used, decision support utilizes the regression model to make a statement about the most appropriate k-values for the situation to improve performance. The values are used for a defined period of time and re-evaluated afterwards

It is necessary to evaluate whether and to what degree the variation occurs due to the inherent stochastic uncertainties of the simulation model. The simulation study can further evaluate how the frequency of adjustment affects performance.

A parameter analysis is performed in this context to find out which observations have significant influence, and which do not. Data pre-processing such as standardization, one-hot encoding, and a combination of these are performed independently of the method used, but due to the simulation focus, their consequences are not evaluated in detail.

3 Evaluation

For the training data set, a parameter study was performed recording all possible combinations of k_1-values from 1 to 10 and k_2-values from 0.01 to 1.01 under 7 different workloads from 85 % to 95 % as well as 12 different product mixes with different setup proportions.

For each of the 9240 individual parameter combinations, 5 replications were performed. The data set used thus comprises 46200 samples. The observations from the system were the average mean tardiness, average lead time, product mix, and average machine utilization. In this contribution, the k-values, machine utilization, and performance indicators are considered as continuous variables, while the product mix is considered as a categorical variable.

In the raw data, it can be seen that product mixes perform differently at the same utilization rate and using the same static k-values, depending on the setup ratio of the mix, shown for two product mixes in Figure 3. A small k_2-value, which is beneficial for product mixes with high setup ratio (e.g. [30,40,20,10]), would lead to a 30% degradation in performance for product mixes with a lower setup ratio. In this study, a machine utilization of 85 % is considered. It should be mentioned that the raw data shows an increase of up to 5 % utilization depending on the different setup time proportions per product mix, for the same planned utilization. Further, low utilization levels mean that no potential for improvement is possible. This situation must be examined over a number of product mixes in order to improve performance.

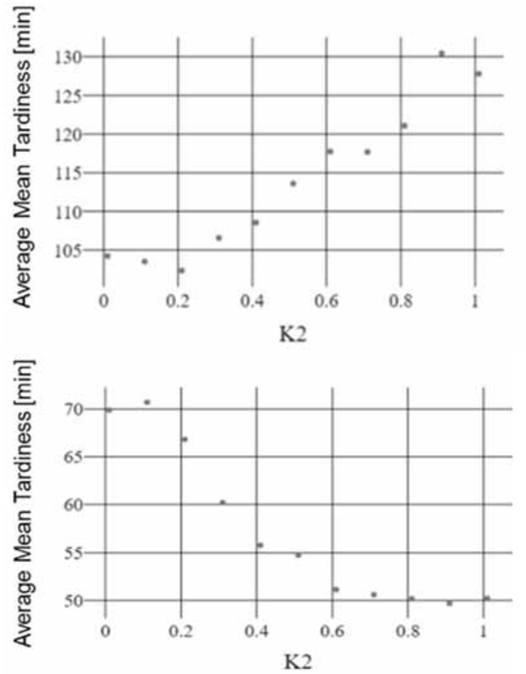

Figure 3: Based on the k_2-values, the performance of product mix [30,40,20,10] (left) and product mix [10,70,10,10] (right) are different given the planned utilization of 85 %.

In addition to the first data set with 46200 data points, a second data set with 13860 data points (corresponding to 30% of the first data set) is generated. Subsequently, the NNs as well as the decision trees (DTs) were trained on both sets to be able to make a statement about the performance with more data points. The parameters for the NNs as well as the DTs were determined using a grid search procedure

The NN was implemented as a multi-layer perceptron in Python using the scikit learn library. The resulting two-layer network with 10 neurons in the first layer and 30 neurons in the second layer had the activation function "relu". In combination with the solver "adam", a mini-batch size of 500 samples showed good results. The initial learning rate was set to 0.01. An L2 regularization was performed.

The DT was implemented using scikit learn as a decision tree regressor in Python. In this framework, it was found that using a maximum depth of 5, with at least 4 samples per leaf led to good results.

The RL agent was trained using the Pathmind software-as-a-service platform with 12000 simulation runs. For training, the discrete-event simulation model was exported as a stand-alone Java file and trained on the platform, independent of local resources for 12 hours.

During this process, various hyperparameter configurations were automatically evaluated as part of population-based training and the best configuration for the scenario was found. Pathmind uses Ray and RLlib for training the agent. The strategy of the agent was trained by Proximal Policy Optimization

As part of the evaluation, the three methods are tested in online use in the context of the event discrete simulation. This involves documenting performance for a known scenario with a static workload and a known product mix. In the following, the scenario is a workload of 85% and product mix [30,40,20,10] from above. Figure 4 shows an example of the agent's behavior trained with reinforcement learning. As seen above, a low k_2-value is beneficial for the product mix [30,40,20,10]. It can be clearly seen that when the average delay (left Y-axis) in the system varies over time (X-axis), the used k_2-values of the ATCS rule (right Y-axis) is adjusted.

Over 30 replications, for a static utilization and for a known product mix, dynamic adjustment of k-values with RL has a positive impact but is not significantly different from static selection of k-values.

Of particular interest (see Figure 5) is the poor performance of the NNs; it is reasonable to assume that the dynamic selection and adjustment of the rules by the NNs has a negative impact on performance in the static scenario (Priore et al. 2006)

In the second evaluation scenario for the dynamic adjustment, a static utilization with changing product mixes is evaluated. In the scenario, a new product mix (in this case product mix [10,70,10,10]) is considered in the system over ¼ of the simulation time. It can be seen in Figure 6 that the selection of good static k-values already leads to good performance. In comparison, the DTs, the NNs as well as the RL agent bring an additional significant improvement of up to 15 %. Additionally, the RL agent is still 3 % better than the DTs. In contrast to the static scenario, the NN can show its advantages regarding generalizability of behavior. The comparable performance of RL and NN is understandable since RL uses NNs to estimate the reward.

Over the evaluation in both scenarios, it is shown that DTs can reproduce known system behavior very well and can describe dynamic behavior to some extent.

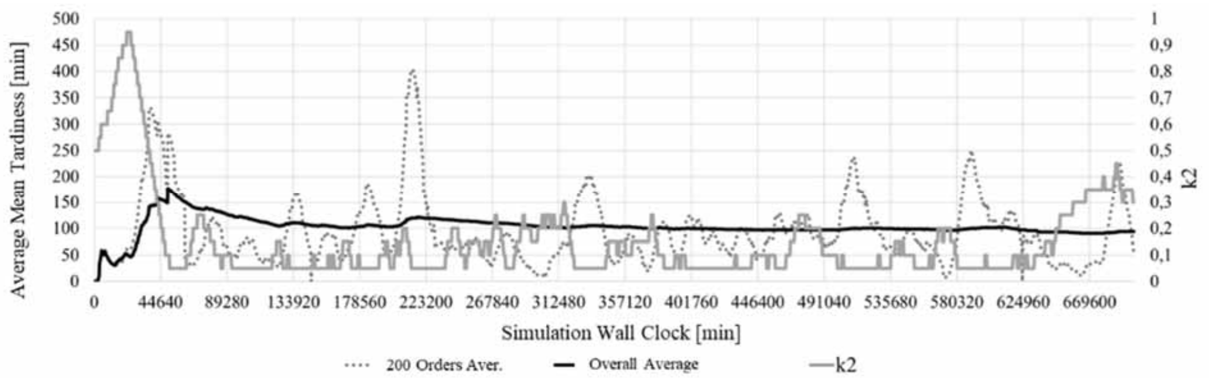

Figure 4: The RL-agent adjusts the k_2-value based on the system status dynamically.

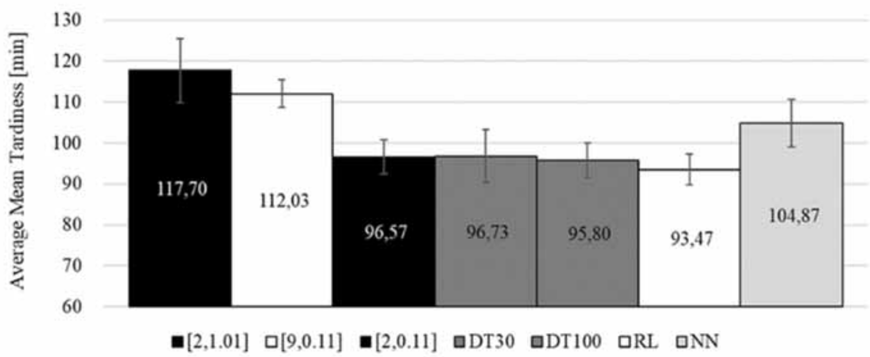

Figure 5: The direct comparison shows the performance with static as well as dynamically adjusted k-values by the DT, NN and the RL approach in a known scenario.

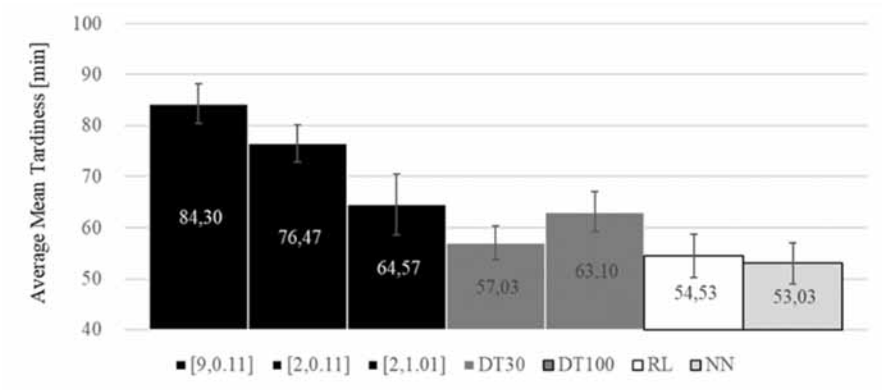

Figure 6: The direct comparison shows the performance with static as well as dynamically adjusted k-values by the DT, NN and the RL approach in an unknown scenario.

The use of NNs and RL is especially advantageous in scenarios with unknown behavior and can lead to an improvement in performance of up to 15%.

4 Summary and Outlook

Dynamic adaptation of priority rules using various machine learning methods can lead to improved performance. In this paper, three methods for adjusting the k-values of the ATCS rule were trained and evaluated over two scenarios. A data set which includes the relationships between product mix, k-values, and system utilization was created using a flow shop manufacturing environment and an extensive parameter study. This was then used as the training basis for DT and NN, while the discrete-event model was used as the training environment for the RL agent.

The comparison within the static scenario shows that DT and RL can reproduce the performance of the static k-values. During training, it was shown that the use of DTs can help in making qualitative statements regarding performance. In the dynamic scenario, it was shown that all three methods can improve the performance. On par, RL and NN can reduce average delay by 15% and compensate for unplanned product mix changes. In the next step, a deep and detailed analysis of the dynamic adjustment over multiple product mixes and unknown scenarios will be performed

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EUROSIM Data and Quick Info

VESS – Virtual EUROSIM Seminar

Virtual Simulation Presentations, since June 2020 www.eurosim2023.eu

ASIM SPL 2023

20th ASIM Dedicated Conference on Simulation in Production and Logistics

September 13-15, 2023, Ilmenau, Germany www.asim-fachtagung-spl.de

1. ASIM Anwendertagung *Simulation in Produktion und Logistik*

September 14-15, 2022, Erlangen, Germany

www.faps-ipc.de/veranstaltungen/1-asim-anwendertagung/

SIMS 2022

63rd International Conference of Scandinavian Simulation Society

Sept. 20-21, 2022, Trondheim, Norway scansims.org

EUROSIM CONGRESS 2023

June 28-30, 2023, Amsterdam, The Netherlands www.eurosim2023.eu

Contents

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EUROSIM Federation of European Simulation Societies

General Information. **EUROSIM**, the Federation of European Simulation Societies, was set up in 1989. The purpose of **EUROSIM** is to provide a European forum for simulation societies and groups to promote modelling and simulation in industry, research, and development – by publication and conferences. → *www.eurosim.info*

Member Societies. **EUROSIM** members may be national simulation societies and regional or international societies and groups dealing with modelling and simulation. At present **EUROSIM** has *Full Members* and *Observer Members* (*), and *Member Candidates* (**).

ASIM	Arbeitsgemeinschaft Simulation *Austria, Germany, Switzerland*
CEA-SMSG	Spanish Modelling and Simulation Group; *Spain*
CSSS	Czech and Slovak Simulation Society *Czech Republic, Slovak Republic*
DBSS	Dutch Benelux Simulation Society *Belgium, Netherlands*
KA-SIM	Kosovo Simulation Society, *Kosovo*
LIOPHANT	LIOPHANT Simulation Club; *Italy & International*
LSS	Latvian Simulation Society; *Latvia*
PSCS	Polish Society for Computer Simulation; *Poland*
NSSM	Russian National Simulation Society *Russian Federation*
SIMS	Simulation Society of Scandinavia *Denmark, Finland, Norway, Sweden*
SLOSIM	Slovenian Simulation Society; *Slovenia*
UKSIM	United Kingdom Simulation Society *UK, Ireland*
ALBSIM	Albanian Simulation Society*; *Albania*
ROMSIM	Romanian Society for Modelling and Simulation*; *Romania*
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CROSSIM	*Croatian Society f. Simulation Modeling;* Croatia
FRANCOSIM	*Société Francophone de Simulation* *Belgium, France*
HSS	*Hungarian Simulation Society;* Hungary
ISCS	*Italian Society for Computer Simulation, Italy*

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SNE – Simulation Notes Europe. **SNE** is **EUROSIM**'s scientific journal with peer reviewed contributions as well as a membership journal for **EUROSIM** with information from the societies. **EUROSIM** societies distribute **SNE** (electronic or printed) to their members as official membership journal. **SNE** Publishers are **EUROSIM**, **ARGESIM** and **ASIM**.

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EUROSIM Congress and Conferences.

Each year a major **EUROSIM** event takes place, the **EUROSIM CONGRESS** organised by a member society, **SIMS EUROSIM Conference**, and **MATHMOD Vienna Conference (ASIM)**.

EUROSIM Congress 2019, the *10th EUROSIM Congress*, was organised by **CEA-SMSG**, the Spanish Simulation Society, in La Rioja, Logroño, Spain, July 1-5, 2019;

Due to Covid-19 virus some **EUROSIM** events had to be cancelled in 2020 or 2021, resp. To bridge this gap, **EUROSIM** is organising the series **VESS - Virtual EUROSIM Simulation Seminar** – seminars by simulation professionalists (2 hours via web), in preparation for upcoming **EUROSIM** events. → ***www.eurosim2023.eu***

Next main event is **SIMS 2022 Trondheim**. This **EUROSIM Conference** is organized by **SIMS**, the Scandinavian Society,
SIMS 2022, The 63rd International Conference of Scandinavian Simulation Society, will be organized in Trondheim, Norway, September 20-21, 2022
→ ***scansims.org***

EUROSIM Congress 2023, the *11th EUROSIM Congress*, will be organised by **DBSS**, the Dutch Benelux simulation society, in Amsterdam, June 28-30, 2023.
→ ***www.eurosim2023.eu***

Furthermore, **EUROSIM Societies** organize also local conferences, and **EUROSIM** co-operates with the organizers of the **I3M Conference Series.**
→ ***www.liophant.org/conferences/***

EUROSIM Member Societies

ASIM
German Simulation Society
Arbeitsgemeinschaft Simulation

ASIM (Arbeitsgemeinschaft Simulation) is the association for simulation in the German speaking area, servicing mainly Germany, Switzerland and Austria. **ASIM** was founded in 1981 and has now about 400 individual members (including associated), and 90 institutional or industrial members.

→ *www.asim-gi.org* with members' area

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ASIM is organising / co-organising the following international conferences:

- **ASIM SPL** Int. Conference 'Simulation in Production and Logistics' – biannual
  ASIM SPL 2023 20th ASIM SPL, Sept. 13-15, 2023, Ilmenau, Germany ***www.asim-fachtagung-spl.de***
- **ASIM SST** 'Symposium Simulation Technique' – biannual
- **MATHMOD** Int. Vienna Conference on Mathmatical Modelling – triennial

Furthermore, **ASIM** is co-sponsor of *WSC* - Winter Simulation Conference, of SCS conferences *SpringSim* and *SummerSim*, and of *I3M* and *Simutech* conference series.

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STS	Simulation of Technical Systems Walter Commerell, *commerell@hs-ulm.de*
SPL	Simulation in Production and Logistics Sigrid Wenzel, *s.wenzel@uni-kassel.de*
EDU	Simulation in Education/Education in Simulation A. Körner, *andreas.koerner@tuwien.ac.at*
BIG DATA	Working Group Data-driven Simulation in Life Sciences; *niki.popper@dwh.at*
WORKING GROUPS	Simulation in Business Administration, in Traffic Systems, for Standardisation, etc.

CEA-SMSG – Spanish Modelling and Simulation Group

CEA is the Spanish Society on Automation and Control and it is the national member of IFAC (International Federation of Automatic Control) in Spain. Since 1968 **CEA-IFAC** looks after the development of the Automation in Spain, in its different issues: automatic control, robotics, *SIMULATION*, etc. The association is divided into national thematic groups, one of which is centered on Modeling, Simulation and Optimization, constituting the **CEA** Spanish Modeling and Simulation Group (**CEA-SMSG**). It looks after the development of the Modelling and Simulation (M&S) in Spain, working basically on all the issues concerning the use of M&S techniques as essential engineering tools for decision-making and optimization.

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CSSS – Czech and Slovak Simulation Society

CSSS -The *Czech and Slovak Simulation Society* has about 150 members working in Czech and Slovak national scientific and technical societies (*Czech Society for Applied Cybernetics and Informatics*, *Slovak Society for Applied Cybernetics and Informatics*). **CSSS** main objectives are: development of education and training in the field of modelling and simulation, organising professional workshops and conferences, disseminating information about modelling and simulation activities in Europe. Since 1992, **CSSS** is full member of **EUROSIM**.

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DBSS – Dutch Benelux Simulation Society

The *Dutch Benelux Simulation Society* (**DBSS**) was founded in July 1986 in order to create an organisation of simulation professionals within the Dutch language area. **DBSS** has actively promoted creation of similar organisations in other language areas. **DBSS** is a member of **EUROSIM** and works in close cooperation with its members and with affiliated societies.

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LIOPHANT Simulation

Liophant Simulation is a non-profit association born in order to be a trait-d'union among simulation developers and users; Liophant is devoted to promote and diffuse the simulation techniques and methodologies; the Association promotes exchange of students, sabbatical years, organization of International Conferences, courses and internships focused on M&S applications.

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LSS – Latvian Simulation Society

The Latvian Simulation Society (LSS) has been founded in 1990 as the first professional simulation organisation in the field of Modelling and simulation in the post-Soviet area. Its members represent the main simulation centres in Latvia, including both academic and industrial sectors.

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KA-SIM Kosovo Simulation Society

Kosova Association for Modeling and Simulation (KA-SIM, founded in 2009), is part of Kosova Association of Control, Automation and Systems Engineering (KA-CASE). KA-CASE was registered in 2006 as non Profit Organization and since 2009 is National Member of IFAC – International Federation of Automatic Control. KA-SIM joined EUROSIM as Observer Member in 2011. In 2016, KA-SIM became full member.
KA-SIM has about 50 members, and is organizing the international conference series International Conference in Business, Technology and Innovation, in November, in Durrhes, Albania, and IFAC Simulation Workshops in Pristina.

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NSSM – National Society for Simulation Modelling (Russia)

NSSM - The Russian National Simulation Society (Национальное Общество Имитационного Моделирования – НОИМ) was officially registered in Russian Federation on February 11, 2011. In February 2012 NSS has been accepted as an observer member of **EUROSIM**, and in 2015 NSSM has become full member.

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PSCS – Polish Society for Computer Simulation

PSCS was founded in 1993 in Warsaw. PSCS is a scientific, non-profit association of members from universities, research institutes and industry in Poland with common interests in variety of methods of computer simulations and its applications. At present PSCS counts 257 members.

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SIMS – Scandinavian Simulation Society

SIMS is the *Scandinavian Simulation Society* with members from the five Nordic countries Denmark, Finland, Iceland, Norway and Sweden. The SIMS history goes back to 1959. SIMS practical matters are taken care of by the SIMS board consisting of two representatives from each Nordic country (Iceland one board member).

SIMS Structure. SIMS is organised as federation of regional societies. There are **FinSim** (Finnish Simulation Forum), **MoSis** (Society for Modelling and Simulation in Sweden), **DKSIM** (Dansk Simuleringsforening) and **NFA** (Norsk Forening for Automatisering).

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SLOSIM – Slovenian Society for Simulation and Modelling

SLOSIM - Slovenian Society for Simulation and Modelling was established in 1994 and became the full member of **EUROSIM** in 1996. Currently it has 90 members from both Slovenian universities, institutes, and industry. It promotes modelling and simulation approaches to problem solving in industrial as well as in academic environments by establishing communication and cooperation among corresponding teams.

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Last data update December 2018

UKSIM - United Kingdom Simulation Society

The UK Simulation Society is very active in organizing conferences, meetings and workshops. UKSim holds its annual conference in the March-April period. In recent years the conference has always been held at Emmanuel College, Cambridge. The Asia Modelling and Simulation Section (AMSS) of UKSim holds 4-5 conferences per year including the EMS (European Modelling Symposium), an event mainly aimed at young researchers, organized each year by UKSim in different European cities. Membership of the UK Simulation Society is free to participants of any of our conferences and their co-authors.

→*uksim.info*

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Last data update March 2020

EUROSIM Observer Members

ROMSIM – Romanian Modelling and Simulation Society

ROMSIM has been founded in 1990 as a non-profit society, devoted to theoretical and applied aspects of modelling and simulation of systems.

→ *www.eurosim.info/societies/romsim/*

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Last data update June 2019

ALBSIM – Albanian Simulation Society

The Albanian Simulation Society has been initiated at the Department of Statistics and Applied Informatics, Faculty of Economy at the University of Tirana, by Prof. Dr. Kozeta Sevrani. The society is involved in different international and local simulation projects, and is engaged in the organisation of the conference series ISTI - Information Systems and Technology. In July 2019 the society was accepted as EUROSIM Observer Member.

→ *www.eurosim.info/societies/albsim/*

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Last data update July 2019

Societies in Re-organisation / Former Societies

The following societies are at present inactive or under re-organisation:

- CROSSIM – *Croatian Society for Simulation Modelling*
  Contact: Tarzan Legović, *Tarzan.Legovic@irb.hr*
- FRANCOSIM – Société Francophone de Simulation
- HSS – Hungarian Simulation Society
- ISCS – Italian Society for Computer Simulation

The following societies have been formally terminated:

- MIMOS –Italian Modeling & Simulation Association; terminated end of 2020.

HSS – Hungarian Simulation Society

There are plans to reactivate Hungarian Simulation Society. M. Mujica Mota EUROSIM President, is in contact with Andrási Gábor, Head of the Dean's office at the Faculty of International Management and Business of Budapest Business School University of Applied Sciences (BBS). We ask interested people to contact Mr. Gábor, *andrasi.gabor@uni-bge.hu*.

Association Simulation News

ARGESIM is a non-profit association generally aiming for dissemination of information on system simulation – from research via development to applications of system simulation. **ARGESIM** is closely co-operating with **EUROSIM**, the Federation of European Simulation Societies, and with **ASIM**, the German Simulation Society. **ARGESIM** is an 'outsourced' activity from the *Mathematical Modelling and Simulation Group* of TU Wien, there is also close co-operation with TU Wien (organisationally and personally).

→ *www.argesim.org*

→ *office@argesim.org*

→ ARGESIM/Math. Modelling & Simulation Group,
Inst. of Analysis and Scientific Computing, TU Wien
Wiedner Hauptstrasse 8-10, 1040 Vienna, Austria
Attn. Prof. Dr. Felix Breitenecker

ARGESIM is following its aims and scope by the following activities and projects:

- Publication of the scientific journal **SNE** – *Simulation Notes Europe* (membership journal of **EUROSIM**, the *Federation of European Simulation Societies*) – *www.sne-journal.org*
- Organisation and Publication of the **ARGESIM Benchmarks** for *Modelling Approaches and Simulation Implementations*
- Publication of the series **ARGESIM Reports** for monographs in system simulation, and proceedings of simulation conferences and workshops
- Publication of the special series **FBS Simulation** – Advances in Simulation / Fortschrittsberichte Simulation - monographs in co-operation with ASIM, the German Simulation Society
- Support of the Conference Series **MATHMOD Vienna** (triennial, in co-operation with **EUROSIM**, **ASIM**, and **TU Wien**) – www.mathmod.at
- Administration of **ASIM** (German Simulation Society) and administrative support for **EUROSIM** *www.eurosim.info*
- Simulation activities for TU Wien

ARGESIM is a registered non-profit association and a registered publisher: **ARGESIM Publisher Vienna**, root ISBN 978-3-901608-xx-y, root DOI 10.11128/z…zz.zz. Publication is open for **ASIM** and for **EUROSIM Member Societies**.

SNE – Simulation Notes Europe

The scientific journal **SNE** – *Simulation Notes Europe* provides an international, high-quality forum for presentation of new ideas and approaches in simulation – from modelling to experiment analysis, from implementation to verification, from validation to identification, from numerics to visualisation – in context of the simulation process. **SNE** puts special emphasis on the overall view in simulation, and on comparative investigations.
Furthermore, **SNE** welcomes contributions on education in/for/with simulation.

SNE is also the forum for the **ARGESIM Benchmarks** on *Modelling Approaches and Simulation Implemen-tations* publishing benchmarks definitions, solutions, reports and studies – including model sources via web.

→ *www.sne-journal.org,*

→ *office@sne-journal.org, eic@sne-journal.org*

→ SNE Editorial Office
ARGESIM/Math. Modelling & Simulation Group,
Inst. of Analysis and Scientific Computing, TU Wien
Wiedner Hauptstrasse 8-10, 1040 Vienna, Austria
EiC Prof. Dr. Felix Breitenecker

SNE, primarily an electronic journal, follows an open access strategy, with free download in basic layout. **SNE** is the official membership journal of **EUROSIM**, the *Federation of European Simulation Societies*. Members of **EUROSIM Societies** are entitled to download **SNE** in high-quality, and to access additional sources of benchmark publications, model sources, etc. On the other hand, **SNE** offers **EUROSIM Societies** a publication forum for post-conference publication of the society's international conferences, and the possibility to compile thematic or event-based **SNE Special Issues**.

Simulationists are invited to submit contributions of any type – *Technical Note*, *Short Note*, *Project Note*, *Educational Note*, *Benchmark Note*, etc. via **SNE**'s website:

→ *www.sne-journal.org,*

EUROSIM 2023:

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June 28-30, 2023, Amsterdam, The Netherlands

The 11th edition of the EUROSIM Congress is dedicated to a sustainable future. And there is no better place than Amsterdam for celebrating the link between simulation and sustainability. You will be pleased to discover the fascinating and vibrant city of Amsterdam, a hub for many sectors such as logistics, ICT, art, financial and business services, fashion, and many others.

Authors are welcome to submit their contributions to the following, but not limited to areas such as:
Agent-Based Simulation ● Methodology ● Supply Chain Management, Logistics & Transportation ● Industrial Case Studies ● Complex, Intelligent, Adaptive and Autonomous Systems (CIAAS) ● Data Science for Simulation ● Environment and Sustainability Applications ● Gaming ● Healthcare Applications ● Hybrid Simulation ● Manufacturing Applications ● Military Applications ● Simulation in Education ● Simulation-Optimization ● Advanced Tutorials/workshops from academics and industry, PhD Track and many more

Paper deadlines and requirements:

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- Discussing paper (2-page extended abstract); peer-reviewed; accepted for presentation
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Instructions, information, submission forms, and procedures are available on the EUROSIM 2023 website ***www.eurosim2023.eu***. Each accepted contribution requires a paid registration.

Important dates:

● Extended abstract/ Full paper submission deadline:	30 November 2022
● Notification of acceptance:	28 February 2023
● Final paper submission deadline:	31 March 2023
● Early bird registration deadline:	30 April 2023
● Last call for registration deadline:	31 May 2023
● EUROSIM Congress 2023:	28-30 June 2023

Submit your paper at: ***https://easychair.org/conferences/?conf=eurosim2023***

ASIM ANWENDER-TAGUNG

Die zunehmende Digitalisierung im täglichen Leben macht keinen Halt vor dem Maschinenbau. Während es für viele von uns fast schon zum Alltag gehört, mit dem Smartphone die Jalousien oder die Waschmaschine zu steuern, werden die Auswirkungen der Digitalisierung im Maschinenbau erst jetzt immer deutlicher. Die heutigen Anforderungen an Produktionsanlagen heutzutage sind vielseitig. Kürzere Produktlebenszeiten führen zu flexibleren, rekonfigurierbaren Anlagen, während kürzere „time-to-market" schnelle Hochläufe der Produktionsanlagen erfordern.

Die zweitägige Anwendertagung „Simulation in Produktion und Logistik – im täglichen Einsatz in der Industrie" bietet die Gelegenheit, mit Simulationsexpertinnen und -experten, innovativen Technologie-anbietern, sowie kreativen Wissenschaftlerinnen und Wissenschaftlern den Einsatz und die Heraus-forderungen von Simulation im täglichen industriellen Umfeld zu diskutieren. Der Fokus der Tagung liegt im Austausch untereinander und in der Anwendung von Methoden und Werkzeugen in der Praxis. Im Rahmen der Anwendertagung wird eine begleitende Ausstellung angeboten; verschiedene Industrie-unternehmen werden Table-top-Präsentationen ausstellen.

www.faps-ipc.de/veranstaltungen/1-asim-anwendertagung/

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www.asim-fachtagung-spl.de/

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