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Dynamic integrated simulative layout planning and production control for matrix production in a semiconductor environment

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Abstract

Increasing complexity, emerging manufacturing objectives and rising costs of manufacturing equipment result in the needs for faster product development and for a more effectively use manufacturing equipment through flexible and reconfigurable operations. Semiconductor manufacturing constitutes a prime example and is prone to frequent breakdowns and changes in product portfolio and manufacturing system. Matrix production offers adaptable routing and modular configurations, thereby enhancing flexibility and adaptability in streamlining material and process flows. While both planning the layout and the production control through scheduling and dispatching of such systems has been extensively studied, there remains a need for more thorough exploration of integrated optimization strategies encompassing both manufacturing layout planning and production control. The proposed approach optimizes multiple criteria through layout planning and production control of a matrix production by formulating a multi-objective optimization approach and using the NSGA-II for optimization to identify the balanced solutions. To confirm the efficacy of the proposed method, we applied it to both a generalized matrix production simulation and a real-world semiconductor use case. Our results, visualized in Pareto fronts, illuminate the inherent trade-offs within manufacturing objectives.

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1. Introduction

Manufacturing of the future needs flexibility and changeability from product design throughout all manufacturing areas [1] to dynamically react to a highly volatile environment. Increasingly dynamic manufacturing stemming from demand, regulation and the possibility to include a circular economy require changes in product portfolio leading to more complex manufacturing environments that facilitate matrix production [2]. At the same time it becomes apparent that the design of manufacturing systems and the ability to reconfigure instead of rebuilding from scratch has strong effects on sustainability [3]. Thus, reconfigurable manufacturing systems provide a promising path to deal with these increasing dynamics [4], especially coupled with reconfigurability extension into production networks [5].

Matrix production systems make up the most sophisticated and widely used implementation of this reconfigurability on production system level [6]. Matrix production, with its flexi-

ble and modular setup, addresses these challenges by enabling simultaneous production of multiple products on shared assets, such as Automated Guided Vehicles (AGVs), to streamline material flows and optimize resource utilization and overall productivity. This versatility allows for quick reconfiguration of production lines to respond promptly to changing market trends and unforeseen disruptions, ensuring competitiveness and resilience in fast-paced environments.

While the extensive planning of such matrix production and reconfigurable systems has been widely studied [7], production control itself is likewise frequently studied, in particular in matrix production systems [8]. Besides production control, layout planning is crucial for matrix production as it determines the spatial arrangement of manufacturing stations and resources, optimizing material flow, minimizing transportation distances, and facilitating efficient utilization of shared assets, thereby amplifying flexibility beyond the scope of production control alone [9]. The performance of matrix production hinges upon the synergistic coordination of decisions of both layout planning and production control, which has been neglected in the existing studies.

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In this study, we extend the current research landscape in matrix production by formulating optimization models to tackle two primary challenges: the layout planning problem and the selection of scheduling and dispatching. Our evaluation encompasses a comprehensive assessment of matrix production performance across various objectives, including utilization, throughput, delay, among others, aimed at thoroughly evaluating decisions in the context of a highly volatile production environment. In this contribution, an approach is suggested enabling a joint consideration of both using a practical example that incorporates the aforementioned complexities. These complexities culminate in semiconductor manufacturing [10] making it an ideal system to study such a dynamic integrated layout planning and production control.

The paper is structured as follows: [section 2](#) introduces the state-of-the-art in layout planning for matrix production and related systems, as well as the corresponding typical production control selections. The proposed integrated, dynamic simulative layout planning and production control is presented in [section 3](#). It is validated in simulation studies and a real-world semiconductor case in [section 4](#). The results are discussed in [section 5](#) and concluded with an outlook in [section 6](#).

2. State-of-the-art

2.1. Layout planning in matrix production

Layout planning in manufacturing is the process to determine a relative location among equipment and assets in the manufacturing system [11]. Both forms with predefined locations [11] and flexible layout arrangements [12] are equally present. Nowadays, using simulations to plan manufacturing systems and their respective layout is a state-of-the-art approach [13]. In this case the dynamic behavior of the manufacturing system given a selected layout is analyzed and iteratively, often manually, improved [13]. Matrix production systems offer a much higher degree of flexibility in material flow than traditional manufacturing systems, which complicates the layout planning process [6]. In general, reconfigurable manufacturing systems require a multi-objective optimization, which can use simulations with genetic algorithms to improve the layout [14]. The integration of planning a layout and the production control at the same time has been neglected in literature, in so far as only basic assumptions about the used production control, in a fixed manner, are assumed [14].

2.2. Production control in matrix production

In the realm of production planning and control the classical job shop problem stands out due to its complexity [15]. Interestingly, layout planning is regarded less frequently in such job shops [16]. Due to the complexity, however, the study of production control, typically heuristics to be adaptable [17] is predominant. Production control in general aims at optimally utilizing available equipment within a manufacturing system through changing the production plan, also called scheduling

[15] or in a real-time manner adapting to the current situation in the production system and taking decisions about the material flow one by one [18]. In matrix production systems the usage of priority rules, such as first-in-first-out (FIFO), shortest processing time (SPT), earliest due date (EDD) and nearest job first (NJJ), have gained popularity and represent the state of the art [19]. Thereby, the semiconductor manufacturing perfectly mirrors a use case with the aforementioned challenges [17].

2.3. Multi-objective optimization in matrix production

Matrix production systems often involve multiple objectives [14], such as minimizing lead time, maximizing throughput, reducing costs, and reducing emissions. Multi-objective optimization techniques are employed to find optimal solutions that balance trade-offs between these objectives [20]. The Non-dominated Sorting Genetic Algorithm II (NSGA-II) has emerged as a popular and effective method for solving multi-objective optimization problems [21]. The integration of NSGA-II with simulation models has proven to be a powerful approach for evaluating and optimizing production systems [12, 14]. However, the application of NSGA-II in the context of matrix production systems has been limited. In particular, the simultaneous optimization of layout planning and production control strategies using population based algorithms, such as NSGA-II, has not been extensively explored in the literature.

3. Dynamic simulative integrated layout planning and production control

In this section a detailed overview on the selected approach is provided on a highlevel as well as a formalized problem.

3.1. Conceptual approach

Production system design is a decision with major impact on a company's success and imposes challenges on decision makers. The design spans from the selection of resources to the allocation of orders to resources and rules definition. A multitude of options encourages a simulative assessment of decisions and system performance, as it has been, for example, done long time for layout design [9], but also for the evaluation of production control [8]. In our case, a multitude of design parameters is used, which are then used as starting points for a simulation to determine relevant key performance indicators (KPIs). An optimization is applied to further improve system design and to identify the non-dominated solutions. The system design variables chosen may vary. In the approach presented dispatching (transporting orders between machines or equipment), order sequencing (selecting the priority in buffers) and the layout (locations of machines or equipment) are selected as variables.

The machines' positions on the shopfloor are variable and their locations are determined using a tuple of integer numbers indicating their coordinates on the shopfloor, or in predetermined position cases through an allocation. Following the selected policies and positions, a simulation of the complex matrix production system is run as visualized in [Figure 1](#). This is

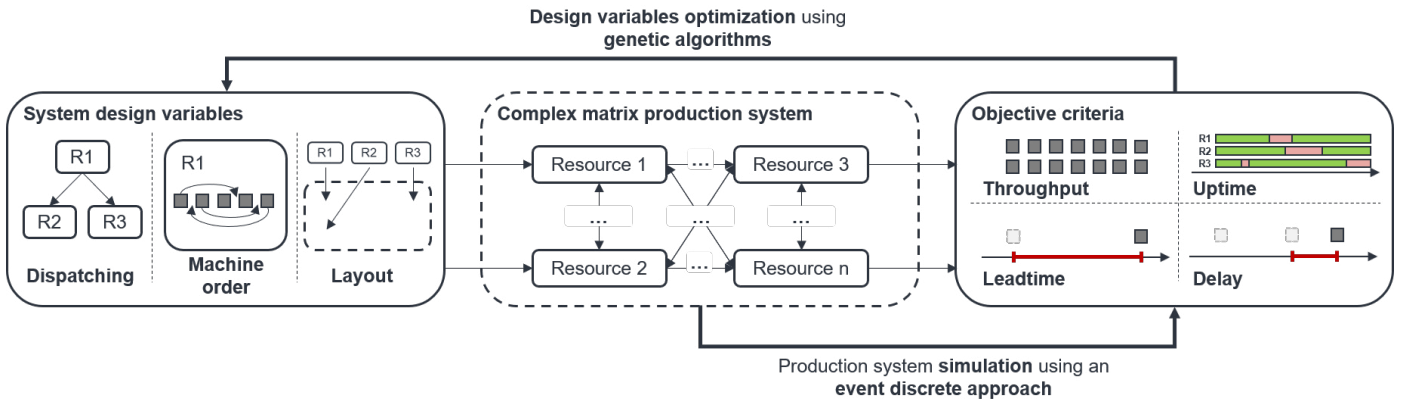


Fig. 1. Conceptual approach

particularly important if transport time is a critical success factor for order completion. In order to evaluate the decisions, several objective criteria are determined during the simulation run. Besides classical multi-objective optimization towards throughput, utilization or delays [15] increasing sustainability, in particular in matrix production systems, is gaining attention [18]. In this case, throughput, utilization, lead time and order delay are selected, however, an extension towards sustainable objectives is possible. The determinants for the production system are encoded to allow the application of a genetic algorithm. In this case, an NSGA-II is used for multi-objective optimization based on a randomized initial population. Sorting the solutions non-dominated solutions can be selected and used for the next generation and therefore the next series of simulation runs. A further specification of the optimization problem is given in the following section.

3.2. Problem formalization

In this section, an optimization model to balance diverse objectives in matrix production is developed. We modeled the matrix production as a system comprising $i \in I$ machines and stations interconnected by Automated Guided Vehicles (AGVs). Both layout planning and production control were considered simultaneously and modeled as two types of decision variables.

For the production control, we define the two decision variables: transportation dispatching rule t , and order sequencing rule m for selecting the optimal transporting schedule of AGVs and production order sequencing. Considering the nature of the matrix production, we consider the transportation dispatching rule (t) to be selected from four alternatives: FIFO, SPT, EDD, and NJF, and the order sequencing rule (m) can be chosen from three alternatives: FIFO, SPT, and EDD. The decision of layout planning is represented by the position (p_i) of each machine, including spatial coordinates in both the x and y dimensions, denoted as $x_i \in \mathbb{R}$ and $y_i \in \mathbb{R}$ respectively, representing the location of each machine within the available factory space.

Each set of decision variables will be assessed using the discrete-event simulation model detailed in Section 3. The decision variables are selected to optimize the following objectives: 1) maximizing throughput f_t : the number of orders processed

per unit time; 2) minimizing delay f_d : the difference between the actual completion time and the due date of orders; 3) maximizing asset utilization rate f_u : the proportion of time each machine is actively processing orders; and 4) minimizing lead time f_l : the total time an order spends in the system from its arrival to its completion. To strike a balance among these objectives, we formulate a multi-objective optimization model as follows:

$$[\text{OM}] \quad \min_{t,m,p_i} (-f_t, f_d, -f_u, f_l) \quad (1a)$$

$$\text{s.t.} \quad t \in [\text{FIFO}, \text{SPT}, \text{EDD}, \text{NJF}] \quad (1b)$$

$$m \in [\text{FIFO}, \text{SPT}, \text{EDD}] \quad (1c)$$

$$p_i = (x_i, y_i), x \in (0, A), y \in (0, B), \forall i \quad (1d)$$

$$f_t = \frac{n - n_0}{t - t_0} \quad (1e)$$

$$f_d = \frac{\sum_{n_0}^n D_n}{n - n_0} \quad (1f)$$

$$f_u = \frac{\sum_i U_i}{I} \quad (1g)$$

$$f_l = \frac{\sum_{n_0}^n L_n}{n - n_0} \quad (1h)$$

where, 1a defines the objective function. Constraints 1b, 1c, 1d defines the scope of decisions, A and B are the upper bound of x and y , respectively. Throughput f_t , as in (1e), is calculated as the number of orders n processed minus the baseline number to reach steady state n_0 , divided by the elapsed time t after reaching this state t_0 . Delay f_d , as in (1f), is calculated by the average of the delays D_n for all orders in steady state. Utilization f_u , as in (1g), is calculated by the average of the machine utilization U_i for all machines. Lead time f_l , as in (1h), is calculated by the average of the lead times L_n for all orders in steady state.

4. Validation

For the validation, we consider a semiconductor matrix production system with a decision space defined by the dimensions

$A = 35$ and $B = 25$. We use Discrete Event Simulation (DES) which has been fit to the real-world semiconductor system in previous studies. The system processes a total of $n = 6000$ orders, and it reaches a steady state after processing $n_0 = 1000$ orders. The production layout consists of $I = 8$ machines, which can be positioned at various locations within the decision space. The objective is to optimize the target KPI of the manufacturing system by selecting appropriate dispatching rules for transportation (t) and order sequencing (m), as well as determining the optimal positions (p_i) for each machine.

4.1. Flexible layout planning and production control selection

In the generalized case a flexible layout is assumed. The optimization model was solved using the NSGA-II algorithm, initializing the process with a population of 200 individuals, which serves as the starting point from which the algorithm begins its search for optimal solutions. Through 200 iterations spanning generations, conducted using Python, Pareto fronts comprising 39 non-dominated solutions were ultimately generated.

4.1.1. Production control

In analyzing the selection of dispatching rules, we first chose decisions that showed the best performance for each individual objective, which are shown in Table 1. The strategy in the first row demonstrates the best performance among all Pareto fronts in terms of throughput f_t and utilization f_u . The strategies in the second and third rows excel in minimizing delay (f_d) and lead time (f_l), respectively. Based on the results, the best performance of a certain individual objective often occurs when applying the same rule for both transportation dispatching and order sequencing. This can be explained by the fact that each rule is designed to align goals between logistics and production scheduling functions, allowing the system to focus on optimizing a single objective effectively. It is noteworthy that each dispatching rule is inherently suited to specific layout pairings. The selection of an appropriate dispatching rule should consider not only the objectives of the system but also the specific layout constraints and designs, to fully harness its efficacy.

Table 1. Optimal Solution for Individual Objectives from Pareto Fronts

t, m	p_i	f_t	f_d	f_u	f_l
SPT, SPT	[12, 11] [21, 14] [17, 15] [16, 8] [24, 12] [26, 9] [24, 4] [24, 13]	0.34	26	0.84	92
EDD, EDD	[23, 15] [11, 14] [13, 18] [15, 13] [12, 12] [18, 11] [15, 14] [18, 10]	0.32	17	0.77	94
FIFO, FIFO	[22, 10] [20, 14] [18, 13] [14, 5] [26, 8] [31, 15] [24, 19] [21, 7]	0.33	22	0.76	90

While the same rules may optimize one objective, it is at the price of lowering other objects. However, combining different rules can help strike a balance among multiple objectives. The selected Pareto fronts presented in Table 2 demonstrate that choosing different dispatching rules for t and m can lead to balanced results. Comparing the performance from Table 1, while applying the SPT rule alone improves throughput

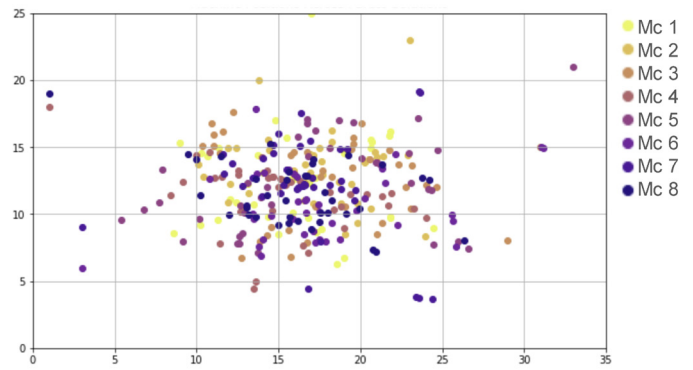


Fig. 2. Machine Positions Across Pareto Solutions

(f_t) and utilization rate (f_u), the combination of NJF and FIFO offers a more balanced solution by improving delay (f_d) at a slight cost to utilization rate. Similarly, using EDD and FIFO rules separately optimizes delay (f_d) and lead time (f_l), respectively. However, combining EDD and FIFO achieves a balanced solution for both objectives (f_d and f_l) without significantly compromising the other two objectives. On the other hand, the combination of SPT and EDD enhances lead time (f_l) while not compromising the other objectives, showcasing the selection trade-off.

Table 2. Balanced Solutions Selected from Pareto Fronts

t, m	p_i	f_t	f_d	f_u	f_l
NJF, FIFO	[17, 25] [23, 23] [31, 15] [1, 18] [33, 21] [3, 6] [3, 9] [1, 19]	0.34	22	0.82	93
EDD, FIFO	[22, 16] [12, 11] [12, 16] [16, 12] [13, 11] [16, 13] [19, 15] [18, 9]	0.33	18	0.81	92
FIFO, EDD	[10, 15] [12, 15] [20, 15] [15, 13] [21, 14] [14, 8] [16, 12] [17, 14]	0.33	20	0.80	92
SPT, EDD	[22, 10] [21, 14] [18, 13] [14, 4] [27, 7] [31, 15] [24, 19] [21, 7]	0.33	23	0.79	91

4.1.2. Layout planning

Following the assessment of dispatching rules, Fig. 2 illustrates the machine position selections for the 8 machines (Mc1 to Mc8) across the Pareto solutions. The positions for each machine are represented using different colors on the graph. It is evident that the machines tend to gravitate towards the center of the factory space, which can be explained by the distance minimization to the in and out queue.

The variation in machine positions across the Pareto solutions further confirms that different dispatching rules may have different optimal positions for the machines. This underscores the significance of the matrix production layout, wherein the flexibility in machine positions enhances adaptability not only to the selected dispatching rules but also to future manufacturing demands. Such adaptability is pivotal in ensuring the resilience and efficacy of manufacturing systems amidst evolving operational requirements and dynamic market conditions.

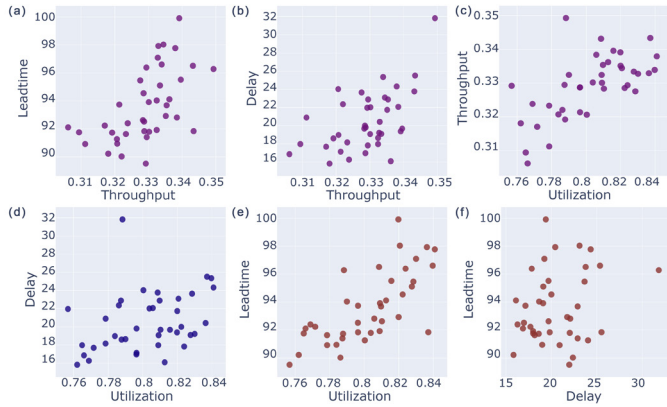


Fig. 3. Pareto Front of Flexible Layout General Case.

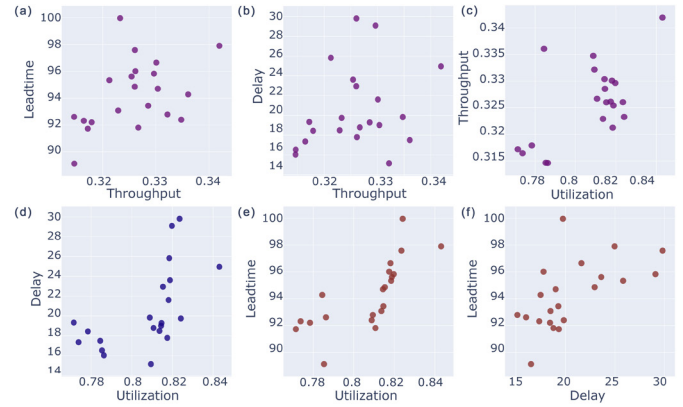


Fig. 4. Pareto Front of Fixed Layout Semiconductor Use-case.

4.1.3. Trade-offs between objectives

Fig. 3 presents the Pareto fronts of the four objectives obtained from the multi-objective optimization. These 2D plots reveal the trade-offs among the objectives. In subplots (a) and (b) as throughput increases, lead time and delay tends to be longer. This can be explained by the fact that higher throughput requires processing more parts simultaneously, resulting in longer waiting times and consequently extended lead times and delays. Moreover, in subplot (c), the positive correlation between throughput and utilization is apparent, as higher throughput necessitates machines to operate at higher capacity to meet the increased demand. Subplot (e) indicates a trade-off between utilization and lead time. As utilization increases, lead time also rises. Machines with higher utilization operate near their full capacity, resulting in longer wait times and lead times. Subplot (d) further reinforces this observation by demonstrating that higher utilization is associated with higher delay. No clear relationship is shown between delay and lead time, as remarked in subplot (c).

4.2. Semiconductor use-case

We evaluate the effectiveness of the model in a real-world semiconductor use case. Due to spatial constraints, instead of allowing unrestricted repositioning of machines throughout the entire factory space, a finite number of predetermined locations (from the actual fab) are allocated for machine placement. According to the data from a local factory, the machine location p_i is selected from the set of predetermined positions P of the machines are as follows, namely, $p_i \in P = \{[1.5, 19], [18.5, 19], [32.7, 23.4], [32.7, 18.3], [30.7, 10.6], [9, 11.3], [11, 11.3], [9, 2.7]\}$. By substituting the constraint (1a) outlined in model [OM], we conducted the optimization for production control and layout planning specific to semiconductor applications.

The selected solutions from the computed Pareto front of the fixed layout use case in Table 3 indicate that layout decisions correlate with delay and lead time. Choosing NJF and SPT achieves the best results for throughput and utilization rate but leads to poor performance in delay and lead time. In

contrast, the combination of EDD and FIFO provides a balanced solution, yielding slightly lower throughput and utilization while maintaining good delay and lead time performance. On the overall evaluation, the manual optimization in the real-world system is Pareto-dominated by the found solutions of the proposed approach with a margin higher than 1%.

Table 3. Solutions Selected from Semiconductor use-case

t, m	p_i	f_t	f_d	f_u	f_l
NJF, SPT	[1, 3, 5, 4, 6, 7, 8, 2]	0.338	27.1	0.840	99.6
FIFO, SPT	[5, 2, 1, 4, 7, 8, 6, 3]	0.325	23.6	0.819	95.6
EDD, EDD	[2, 8, 1, 3, 4, 6, 5, 7]	0.326	18.2	0.777	95.8
EDD, FIFO	[3, 8, 4, 6, 5, 7, 2, 1]	0.327	18.8	0.811	91.8

The Pareto solution from the semiconductor use case is shown in Fig. 4. Comparing these results to Fig. 3, it becomes apparent that the trade-off between utilization and delay, utilization and lead time persists as shown in subplot (d) and (e), respectively. Additionally, in subplot (c), throughput and utilization maintain a weak positive correlation. However, no discernible correlation can be observed between throughput and lead time (subplot (a)). No clear relationship is shown between throughput and delay, delay and lead time, as in subplots (b) and (f). This comparison suggests that layout decisions have a notable impact on the objectives of delay and lead time, leading to less pronounced trade-offs in a fixed layout.

5. Discussion

The results of this study provide valuable insights into the complex dynamics of multi-objective optimization of matrix production systems. The choice of dispatching rules significantly influences the prioritization and objectives. By strategically positioning machines aligned with dispatching rules and prioritized objectives, manufacturers stand to improve the efficiency and effectiveness of their production processes.

The Pareto fronts obtained from the multi-objective optimization reveal the trade-offs among the objectives. The anal-

ysis of these trade-offs highlights the importance of considering balanced Pareto fronts in decision-making. For instance, the trade-off between throughput and lead time as well as utilization and lead time suggests that increasing throughput increases lead times due to the increased processing time and waiting times.

The study also demonstrates the suitability and feasibility of employing the NSGA-II algorithm for multi-objective optimization in matrix production. The algorithm's capability to effectively explore the solution space and generate a diverse set of Pareto-optimal solutions underscores its potential for supporting decision-making in matrix production systems.

6. Conclusion and outlook

The approach selected for a complex matrix production system optimization considers a variety of manufacturing system decision variables (dispatching, order sequence and layout) and uses a simulation to determine the optimal system performance considering multiple objectives, including, throughput, uptime, leadtime, delay. A multi-objective optimization problem is formulated and solved by NSGA-II. The approach is applied in general and validated in a semiconductor use case representing scenarios with flexible layout and fixed layout respectively. For the holistic layout and production control multi-objective optimization an NSGA-II is used. Pareto fronts are created in order to select Pareto optimal solutions. It can be found that for different choice of allocation algorithms (i.e. for dispatching and order sequence) different objectives are in favor. The inclusion of layout design suggests different positions for each dispatching approach. However, a tendency towards the center to minimize transport time is observable.

However, it is essential to acknowledge the limitations of this study. The findings are based on a simulation context and idealized scenario. Future research endeavors should aim to enhance the generalizability of the proposed method by incorporating comprehensive considerations of real-world production constraints and uncertainties. In a next step, the simulatively assessed approach must be transferred to reality. In addition, the KPI system applied can be extended further towards for manufacturing sustainability. Considering KPI, it could be of greater interest to explain the impacts of different system design parameters on these objectives. System description and the degree of modeling detail could be further increased.

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