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OPTIMIZATION OF THE SUBASSEMBLY PRODUCTION PROCESS USING SIMULATION

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Abstract
Using simulation as a tool for production process optimization represents a useful approach to exploring many optimization options which lie ahead on the process improvement path. Previously published research papers report on combining the simulation with another optimization method or a set of manufacturing practices or digital technology. To avoid the complexity of the developed optimization approach in practical application, this paper presents an approach that focuses on grouping the parts first and then simulating the parts group schedule, batch size, and parts interarrival time options to minimize production process cycle time and maximise the output quantity. The developed algorithm was tested with the data from a real case, for the production of the subassembly for the metal frame used in automotive parts logistics. The experimental results show improvements in defined performance parameters for set optimization goal.
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Key Words: Simulation Optimization, Manufacturing, Parts Group Schedule, Batch Size, Interarrival Time, Subassembly Process

1. INTRODUCTION

Staying competitive as a manufacturing company often means being able to produce products by customer demand, respecting the dimensions of process cycle time, costs and product and quality. Adjusting the production process parameters which affect these three dimensions is an activity which can be costly if exercised without careful analysis. Aspects of time, costs and quality are heavily interconnected. Changes in one aspect, for example shortening production cycle time, or repeating certain production operations because of bad quality reflect to the other ones, for example change in costs. Simulation must be concerned as an integral part of this process. The latest reported research papers show that simulation is used increasingly for tracking and optimizing production processes [1] and that it presents an important part of the digitization process in industrial companies [2]. Usually, the production process optimization involves several steps, and the production system simulation model helps to deepen the understanding of the effect of certain parameter changes (for example change in parts production schedule). The feedback in the form of results from the simulation experiment helps in understanding the production system or process response to these internal parameters change. This means that simulation is heavily merged with parameters optimization until the optimization goal is reached and production is put to realization.

Previously reported research papers on cases of application of simulation-based optimization models for production planning and control mainly focused on time and cost minimization with maximal throughput, as shown in a systematic literature review presented by De Sousa Jr. et al. [1]. Finding the right combination of production process parameters and settings is not an easy task, and often it requires combining a simulation model with an additional algorithm, method, management approach, or technology. Liao and Lin [3] show that simulation optimization was used for testing the practicality of the particle swarm algorithm for solving the scheduling problem of automated guided vehicles. The approach presented by Petroodi et al. [4] shows the hybrid method which combines a discrete-event simulation model and a simulated annealing model for optimization of production planning and resource allocation. Ištoković et al. [5] presented an optimization approach combining genetic algorithm and simulation to determine product batch size and schedule for defined batches, and the results show the reduction of production queue waiting times. Istokovic et al. [6] analysed the batch size problem along with the batch schedule for the manufacturing of complex products (the optimization approach included discrete event simulation combined with the genetic algorithm). The combination of simulation and optimization algorithm for solving the scheduling problem was also presented by Jemmali et al. [7]. They integrated simulation with discrete bee colony algorithm to solve scheduling in a two-phase manufacturing flow shop.

Some research papers described the use of simulation optimization in combination with the Taguchi method, for example, to find the optimal combination of process parameters like interarrival time and buffer capacity (with a minimum number of experiments) [8, 9]. A similar approach was used by Sankaran et al. [10] to reduce the cost of the pump manufacturing process, by the means of finding the adequate batch size and interarrival time. Some researchers propose to combine simulation with lean management approach [11-14]. Combination with Value Stream Map (VSM) tool is also used [15, 16], to shorten the production time, reduce work-in-process and increase value-added time for manufacturing processes.

Lately, with the introduction of the Industry 4.0 concept, the role of simulation in the optimization of production processes increased even more [17, 18]. Real-time data, enabled by implementing concepts such as internet-of-things and cyber-physical systems, become more available. Digitization is making simulation a tool for bringing closer the physical manufacturing processes and their virtual models through digital twins [19], but with a notice that more data also means more challenging and complex models, which require accurate real-time data processing for synchronization with physical processes [2, 20].

This paper contributes to production optimization with a representation of the comprehensive approach, which includes schedule, batch size options, and interarrival time analyses. The main idea is to improve the manufacturing process by using data, observation, and analysis with the cooperation of the factory people, without additional investments (like buying additional equipment, additional worker hiring, or introducing additional work hours or work shifts).

The main aspects of the developed approach are understandability and simplicity in its application while enabling the performance of the production system to meet its goals through its optimized processes (applicable to a large number of manufacturing companies that cope with high queue times and the problems of order fulfilment on time). To ease the parameter adjustment problem (parameter change is simpler if there is a lesser number of parts to be considered), the simulation optimization is combined with the group technology approach for forming the parts groups. The group technology approach improves process performance [21], especially when integrated into simulation-based optimization [22, 23]. Created part groups serve as a basis for further improvement.

The presented research shows a real industrial case of simulation-based implementation of a developed methodology for production parameters adjustment, intending to minimize the production cycle time (the time needed to complete the production process from start to finish for a given demand), and to maximize the production output quantity in the production system, by following the approach of simulating the system performance after each optimization step.

The next section describes the developed optimization method and the industrial case setting for method implementation. Simulation experiments and results are presented in section three. Section four gives a conclusion and describes future work for developed method improvements.

2. MATERIALS AND METHODS

The optimization approach has several tasks and decisions with the inclusion of simulation (Fig. 1). Optimization can be done in two phases: initial analysis and optimization goals setup and parameter simulation and optimization.

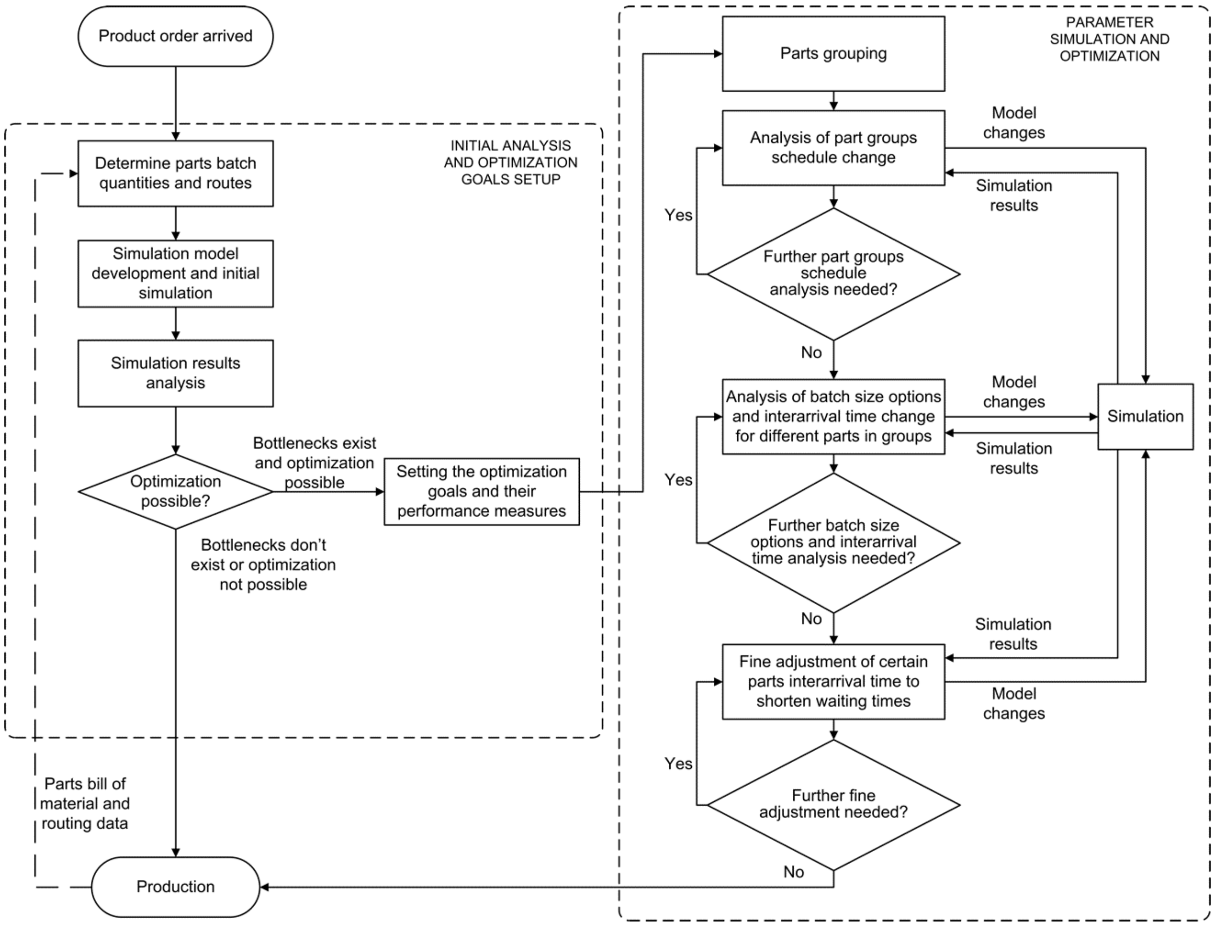

Figure 1: Algorithm of the optimization process.

When the product order comes, the first step is to determine its parts quantities and their routes, by using bills of materials and production operations (production routes) data.

The next step is to develop the simulation model and conduct the initial simulation experiment. The initial simulation results analysis shows the possibility of meeting the given deadline for required product quantities. These results can also show the production bottlenecks. If the production finishes in time and bottlenecks don't exist or there are no optimization possibilities, the optimization process ends here (production can start). Otherwise, the optimization can continue in several steps, but firstly the goals and performance measures need to be set up. The next step, before any optimization is considered, is to form part groups using different criteria. The product parts are grouped, either by parts production operations route similarity, by the geometric shape of parts, or by using another criterion that makes it logical to group parts (for example being a part of the same subassembly). This eases the later optimization options like group scheduling and interarrival rate setup for parts.

When this is done, the optimization can start. Each optimization option can be tested by changing the initial simulation model. The optimization option is used until no further improvements are possible (one analysis can have more iterations). After that, the next optimization steps come. Success criteria for each optimization option are previously set optimization goals and their performance measures.

First comes the analysis of scheduling options for part groups. The aim is to minimize the waiting time bearing the total production cycle time reduction, output quantity maximization, and the existing production bottlenecks (for example, schedule the part groups which need the most production time to go first, etc.).

Next, analyse the batch size and interarrival time for different parts within groups, respecting their quantities (interarrival time represents the time needed between successive batches of parts that are put into production). Large quantities can be split into batches and put into production more frequently. Also, other parts' batch sizes and interarrival times can be set up to follow the change. This helps to avoid unrealistic part quantities on the shop floor in terms of available physical space, and long production waiting times (it is important to communicate with the production planning staff in resolving this issue).

Finally, analyse the effect of fine adjustments of interarrival time and batch sizes for certain parts to further optimize the process (for example, if two different part types go to the same machine, then if waiting occurs, the interarrival time adjustment can shorten the waiting time, influencing later production steps). When this is done, and if no more fine adjustments are necessary, the optimization process ends.

2.1 Case study setup

In the automotive industry, the final product is assembled and dispatched to car dealers. Lots of automotive parts are produced by subcontractors and transported then to main assembly sites. In this supply chain, the timely shipment of parts is influencing the final product assembly. The parts should be correctly packed before transport, which can be done with different types of packaging, with most of them being returnable [24]. The packaging itself is a product that is needed to be produced. It represents an important piece in automotive part logistics and has to satisfy the market demands for durability and quality. Also, the quantity demands must be satisfied. Packaging is used in logistic processes not only for manufacturing but also for after-sales automotive processes, like service and maintenance.

This paper presents the case of the production of a bottom subassembly of a complex metal frame for the needs of automotive parts logistics. The final product serves for packing and securing different automotive parts in transport from one location to another. The factory produces a lot of different products for the needs of automotive parts logistics. The initial screening shows the existence of problems in the job shop including long waiting times and large unfinished production quantities on the shop floor.

The subassembly production consists of two phases, the parts production phase and the assembly phase (this subassembly is later assembled with other sides of the frame to form the final product).

2.2 Determine parts batch quantities and routes

The production environment will be tested for the production order of 300 units, for a time horizon of ten working days, each day represents one 8-hour shift (total for 10 days is 4800 minutes).

Following the first step of the proposed optimization process, it is noted that this subassembly consists of twenty different part types. Parts labels are p1 to p20. Parts batch quantities are presented in Table I. Parts p18, p19, and p20 assemble into part p17. Part p17 then assembles with the other parts into the bottom subassembly of the metal frame.

Workers use boxes or pallets for parts transport between workplaces in the production phase, and a forklift in the assembly phase.

In the parts production phase, initially, some parts are metal pipes or profiles which need to be cut first, and some parts start as metal sheets that also need cutting.

Pipes and profiles are cut with cutting saw machines, and metal sheets are cut with a shearing machine. After cutting, pipe and profile parts are further sent either:

- to the punch press (parts from p1 to p7) and then to the pre-assembly or,
- directly to the pre-assembly (parts from p8 to p15) or,
- to the bending desks (parts p18 and p19), and after the assembly operation of the part p17.

Metal sheet parts (parts p16 and p20) are first sent to the “abkant” press after cutting, and later to the p17 assembly desk (part p20), or directly to the pre-assembly (part p16).

Table I: Part batch quantities for production phase.

Part ID	p1	p2	p3	p4	p5	p6	p7	p8	p9	p10
Quantity	2700	300	1200	1200	600	300	600	600	300	600
Part ID	p11	p12	p13	p14	p15	p16	p17	p18	p19	p20
Quantity	300	600	300	300	3000	600	1200	1200	1200	1200

For each production operation in the production phase, there is one material queue and one or more machines or workplaces. There are three cutting saw machines, two metal shearing machines, five punch presses, three bending desks, one assembly desk for part p17, and one “abkant” press. The assembly phase starts with the pre-assembly of all parts (weakly bonding the parts). All of the part types need to be available before the pre-assembly operation starts. Pre-assembly is then followed by the welding operation. There are seven pre-assembly workplaces and also seven welding workplaces. After welding, the welded bottom subassembly is sent to grinding (there are four grinding workplaces) and finally to the painting operations (there are two painting chambers). All subassemblies are inspected, and if necessary some are sent to rework. For pre-assembly work operation there is one material queue for each part type, and for all other assembly phase work operations there is one queue for each workplace or machine. An initial overview of the production process part routes shows that the production of parts can be carried out in parallel for different part types.

3. SIMULATION EXPERIMENTS AND RESULTS DISCUSSION

3.1 Simulation model development and initial simulation

The simulation model is developed by using Jaamsim open-source software [25, 26], and after the simulation, the results are manually exported to a format appropriate for the spreadsheet software for better visual representation and further analysis. The simulation model is complex, enabling maximum flexibility in terms of machines and parts parameter adjustment. The model was developed by using the data from production routes, product and parts bills of materials, and initial screening (observation) of the process. The machine or workplace service time per part follows the exponential distribution with the minimum, maximum, and mean service time defined for each part type (to replicate the possible variation of real processing or assembly time). All part types are put into production at the same time (respecting their required quantities as shown in Table I). Since there was no splitting of part batch quantities in the initial simulation experiment, there was no need to introduce interarrival times for batches at this point. The initial simulation experiment tests how many units of bottom subassemblies for the complex metal frame can be created when no optimization is included, and it corresponds to the real situation on the shop floor. It also helps to determine possible production bottlenecks. Every simulation experiment is done in 100 replications. The initial simulation experiments show that only between 30 and 32 units can be produced for 4800 minutes. This happens when no optimization is applied, the production phase lasts too long and the parts are waiting for each other at the pre-assembly. Since pre-assembly precedes the longest operation, which is welding, there is no time to finish the bottom subassembly in time. The pre-assembly operation needs to start as soon as possible with the right quantities, to get the units produced for a given amount of time. The optimization goal is to eliminate inefficiencies to produce the required quantity for a minimum of time. Performance measures for this optimization goal are the total amount of time needed for the production of the required quantity of the frame subassembly, and the output quantities of the frame subassembly.

3.2 Parts grouping and schedule analysis for groups

Parts grouping has meaning only in the production phase, because later in the assembly phase there is only subassembly to operate with. Parts were split into four groups, some by the similarity of production route and some by being the parts of another part assembly (like parts needed for the part p17 for example):

- Group A, based on route similarity, consisting of parts p1 to p7;
- Group B, based on route similarity, consisting of parts p8 to p15;
- Group C has only one part which does not fit any other group, consisting of part p16;
- Group D, consisting of parts p18 to p20 because they assemble into part p17.

The criteria for the groups' schedule was shortening the wait time for the pre-assembly operation to start. The machine layout was not changed. The initial simulation results analysis shows that the pre-assembly operation starts late because of waiting for p17 to finish. This puts parts from group D into the first place. After that, using the same criteria, the parts from group A are scheduled, followed by group C, and lastly the parts from group B. By just applying this change, with no investments into additional resources, the output was increased to 120 units. To further reduce waiting time, the batch sizes are changed along with the interarrival times for parts.

3.3 Changing the batch size for parts with large quantities and setting their interarrival times

These changes should enable the availability of parts with the largest quantities or longest production time at the pre-assembly operation. The solution was to look in the part groups for parts that have the largest quantities, divide their quantities into smaller batches, and then determine their interarrival time (determined in consultation with the factory production planner, respecting the constraints of available physical shop floor space for parts).

Using the fact that different parts can be produced side by side, and that preassembly operation starts only when all part types are available, it is noticed that when a part with the large quantity comes to processing all other parts wait for too long, and that is the reason why the preassembly operation starts late. The decision on the part batch size needed several iterative adjustments through simulation (different quantities were tested), and this also required to experiment with different interarrival times.

In group A, the part quantity with the largest batch size was divided into quantities needed for 10 units of the final subassembly. The total quantity for part p1 (2700 pieces) was divided into smaller batches with a quantity of 90 pieces. The same was done in group B for part p15 (3000 pieces), which was divided into batches with 100 pieces. The interarrival time for batches of these part types was determined to be 90 minutes. In group D, the quantities for parts p18, p19, and p20 were divided into batches of 40 pieces (like in group A these are the quantities needed for 10 units of final subassembly), with an interarrival time of 60 minutes. The simulation results for these changes show an increase in the output from 120 units to a range of 224 to 230 units.

3.4 Changing the batch size for the rest of the parts and setting their interarrival times

For other parts in groups (p2 to p7 from group A, p8 to p14 from group B, and p16 from group C), the batch sizes were also adjusted. Their batch quantities were divided to follow the previously introduced changes in large quantity batches (part quantities needed for 10 units of the final sub-assembly). Their interarrival is 90 minutes, to follow the part p1 from group A and part p15 from group B. These changes were simulated and the results show an increase in the output to 300 units. Fig. 2 presents the output production cycle time for each experiment. For this setting, the production cycle times were between 4275 and 4366 minutes, as presented in Fig. 2 a. With this setting, the optimization goal was fulfilled, but it was interesting to see if an additional optimization would shorten the total production cycle time. For that purpose, several simulation experiments were conducted. It was noticed that the total production cycle time can be additionally reduced if there is less transport in the production phase. Total transport done can be influenced by changing the parts batch size. In consultations with the factory production planning staff, it was further experimented with the change of parts batch sizes and interarrival times. For the parts with large quantities (p1, p15, p18, p19, and p20) the batch size and interarrival time were not changed. For parts p2 to p7 from group A, p8 to p14 from group B, and p16 from group C, the batch size was increased to be enough for 20 units of the final subassembly. Their interarrival times were changed from one experiment to another. We experimented with the change of their interarrival times by 30 minutes periods. The solution with the interarrival time of 180 minutes gives the desired unit quantity with the reduction of total time to between 4122 and 4189 minutes (presented in Fig. 2 b). To reduce further this time, additional adjustments are done.

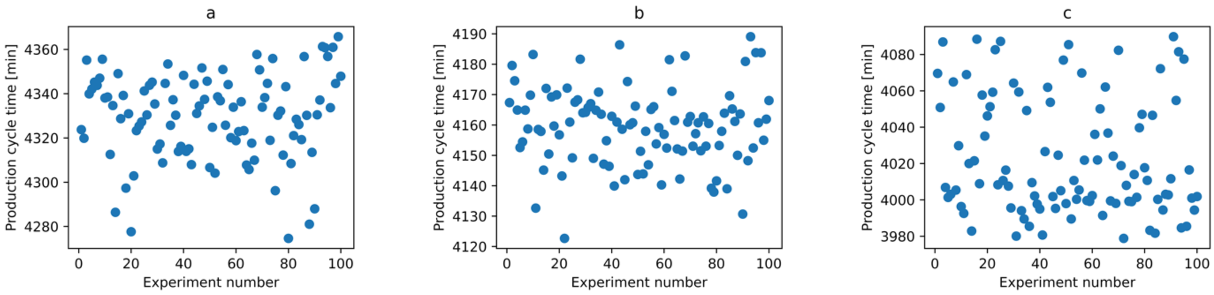

Figure 2: Simulation results for total production cycle time reduction per experiment (total 100 simulation experiments per setting).

3.5 Fine adjustments

By further analysing the production of the parts, it is noticed that parts p16 and p20 have unnecessary waiting on the "abkant" press, which can be avoided by experimenting with the interarrival time for part p20. Because the part p20 needs to be assembled into part p17, the interarrival times for parts p18 and p19 must also follow the change. The interarrival time was fine adjusted through several simulation experiments, resulting in the additional production time reduction. Production time was further reduced to between 3979 and 4090 minutes (presented in Fig. 2 c), with keeping the interarrival time for parts p18, p19, and p20 at 80 minutes.

3.6 Queue times results

Average queue times are presented in Table II. Each column represents the results of one of previously described system experimental settings, starting from the initial state (experimental setting 1), then followed by group schedule (experimental setting 2), large quantities batch size and interarrival time change for 10 units of final subassembly (experimental setting 3), small quantities batch size and interarrival time change for 10 units of final subassembly (experimental setting 4), small quantities batch size and interarrival time change for 20 units of final subassembly (experimental setting 5) and finally fine adjustments for certain parts (experimental setting 6). The average queue times got shorter with the setting of the batch sizes and interarrival times (although, with fine adjustments, the average queue time got a little higher in some of the workplaces). The two painting chambers had no queues, so they are omitted from the results presented in Table II. The two waiting times were tried to additionally get reduced – the waiting time for part p20 at the assembly operation for part p17, and the waiting time for part p16 at the pre-assembly queue. The waiting time for p16 was reduced by changing the interarrival time from 180 to 240 minutes. This reduced the waiting time from an average of 612.84 minutes to 182.17 minutes, while all other results did not change. The waiting time for p20 could not be further optimized. Since the production cycle time was kept within the same boundaries as was in the previous simulation setting, this ended the optimization process.

Table II: Average queue times in minutes for each experiment setting.

	Experimental setting					
Queue	**1**	**2**	**3**	**4**	**5**	**6**
Saw cutting	134.63	134.69	41.03	4.19	5.46	5.46
Punch press	18.60	18.60	6.72	0.58	0.78	0.78
Metal sheet cutting	57.81	57.81	9.81	1.82	2.09	2.10
“Abkant” press	434.83	434.80	49.45	14.11	15.33	15.33
Bending	32.81	32.81	1.01	1.01	1.01	1.01
P17 assembly (p18)	887.15	887.15	292.00	80.22	68.62	78.40
P17 assembly (p19)	887.15	887.15	270.58	42.60	46.69	46.57
P17 assembly (p20)	887.15	887.15	1628.39	553.28	478.62	501.80
Pre-assembly (p1)	1696.24	1580.79	148.14	72.30	51.71	59.70
Pre-assembly (p2)	4546.94	2871.11	2644.98	122.46	184.66	195.03
Pre-assembly (p3)	3033.97	2269.42	2043.22	97.55	139.91	150.29
Pre-assembly (p4)	2832.32	2067.89	1841.63	89.69	125.37	135.75
Pre-assembly (p5)	4112.27	2696.73	2470.59	114.27	170.78	181.16
Pre-assembly (p6)	4481.00	2805.14	2578.99	119.02	179.12	189.49
Pre-assembly (p7)	3900.84	2485.11	2258.93	45.93	155.39	165.77
Pre-assembly (p8)	3720.92	1189.48	1403.44	54.47	76.25	86.65
Pre-assembly (p9)	4391.02	1546.66	1760.72	71.21	104.66	115.06
Pre-assembly (p10)	3379.37	847.13	1061.61	40.54	51.00	61.40
Pre-assembly (p11)	4344.62	1500.26	1714.32	68.51	100.47	110.88
Pre-assembly (p12)	3264.96	732.79	947.22	35.57	42.25	52.66
Pre-assembly (p13)	4286.89	1442.48	1656.48	65.39	95.50	105.90
Pre-assembly (p14)	4229.13	1384.69	1598.72	62.28	90.53	100.94
Pre-assembly (p15)	1435.90	408.20	112.00	23.67	8.26	13.84
Pre-assembly (p16)	4334.11	2008.47	2466.45	767.48	674.01	612.84
Pre-assembly (p17)	363.30	451.28	61.47	569.44	520.61	126.98
Welding (1^{st} workplace)	206.85	831.98	824.43	110.78	121.44	137.17
Welding (2^{nd} workplace)	205.43	830.36	819.95	105.74	112.71	119.06
Welding (3^{rd} workplace)	204.04	828.28	813.02	94.87	110.74	101.62
Welding (4^{th} workplace)	202.12	825.23	802.88	82.93	102.88	92.42
Welding (5^{th} workplace)	202.47	825.37	799.12	77.55	101.61	87.00
Welding (6^{th} workplace)	201.62	823.68	821.79	70.64	103.79	85.20
Welding (7^{th} workplace)	200.59	822.60	818.61	68.62	90.24	77.64
Grinding (1^{st} workplace)	0.40	0.33	0.31	0.31	0.31	0.25
Grinding (2^{nd} workplace)	0.40	0.35	0.33	0.32	0.32	0.25
Grinding (3^{rd} workplace)	0.36	0.36	0.27	0.30	0.30	0.24
Grinding (4^{th} workplace)	0.32	0.29	0.27	0.31	0.31	0.23
Inspection	17.17	17.61	17.61	17.62	17.62	17.62
Rework	0.92	0.88	0.91	0.95	0.95	0.95

3.7 Utilisation results

The utilization of machines and workplaces generally improved both in parts production and assembly phases, as shown in Table III and Table IV respectively (column titles correspond to the ones presented in Table II). By looking at the differences in utilization before and after optimization, it is noted that in the production phase, the utilization improved on average for 12.74 % for saw cutting machines, 0.65 % for punch presses, 0.8 % for shearing machines, 5.71 % for "abkant" press, 0.53 % for bending desks, and 7.16 % for p17 assembly desk.

Table III: Average machine/workplace utilisation in production phase.

	Experimental setting					
Machine or workplace	**1**	**2**	**3**	**4**	**5**	**6**
Cutting saw 1	65.60 %	65.63 %	65.61 %	72.76 %	75.74 %	78.35 %
Cutting saw 2	65.59 %	65.62 %	65.60 %	72.76 %	75.75 %	78.32 %
Cutting saw 3	65.60 %	65.62 %	65.60 %	72.75 %	75.73 %	78.33 %
Punch press 1	3.34 %	3.34 %	3.34 %	3.71 %	3.86 %	3.99 %
Punch press 2	3.34 %	3.34 %	3.34 %	3.71 %	3.86 %	3.99 %
Punch press 3	3.34 %	3.34 %	3.34 %	3.71 %	3.86 %	3.99 %
Punch press 4	3.34 %	3.34 %	3.34 %	3.71 %	3.86 %	3.99 %
Punch press 5	3.34 %	3.34 %	3.34 %	3.71 %	3.86 %	3.99 %
Shearing machine 1	4.14 %	4.14 %	4.14 %	4.59 %	4.77 %	4.94 %
Shearing machine 2	4.14 %	4.14 %	4.14 %	4.59 %	4.77 %	4.93 %
"Abkant" press	29.49 %	29.49 %	29.49 %	32.69 %	34.03 %	35.19 %
Bending desk 1	2.74 %	2.74 %	2.74 %	3.04 %	3.16 %	3.27 %
Bending desk 2	2.74 %	2.74 %	2.74 %	3.04 %	3.16 %	3.27 %
Bending desk 3	2.74 %	2.74 %	2.74 %	3.04 %	3.17 %	3.27 %
P17 assembly desk	36.99 %	36.99 %	36.99 %	41.01 %	42.69 %	44.15 %

Table IV: Average machine/workplace utilisation in assembly phase.

	Experimental setting					
Machine or workplace	**1**	**2**	**3**	**4**	**5**	**6**
Pre-assembly (1st workplace)	11.51 %	17.41 %	17.56 %	19.46 %	20.27 %	20.95 %
Pre-assembly (2nd workplace)	11.51 %	17.44 %	17.49 %	19.39 %	20.24 %	20.86 %
Pre-assembly (3rd workplace)	11.51 %	17.43 %	17.44 %	19.33 %	20.20 %	20.87 %
Pre-assembly (4th workplace)	11.51 %	17.41 %	17.27 %	19.15 %	19.90 %	20.62 %
Pre-assembly (5th workplace)	11.51 %	17.43 %	17.41 %	19.30 %	20.08 %	20.79 %
Pre-assembly (6th workplace)	11.51 %	17.43 %	17.55 %	19.46 %	20.12 %	20.92 %
Pre-assembly (7th workplace)	11.51 %	17.42 %	17.25 %	19.12 %	19.95 %	20.59 %
Welding (1st workplace)	11.18 %	33.49 %	62.13 %	93.58 %	92.33 %	92.91 %
Welding (2nd workplace)	11.13 %	33.45 %	62.08 %	92.80 %	91.71 %	92.20 %
Welding (3rd workplace)	11.07 %	33.39 %	62.02 %	88.68 %	91.53 %	91.62 %
Welding (4th workplace)	11.01 %	33.33 %	61.96 %	86.43 %	90.35 %	91.25 %
Welding (5th workplace)	10.76 %	33.08 %	61.69 %	83.91 %	89.34 %	90.90 %
Welding (6th workplace)	10.68 %	33.00 %	58.94 %	75.02 %	85.71 %	87.79 %
Welding (7th workplace)	10.61 %	32.93 %	58.65 %	67.26 %	70.77 %	86.04 %
Grinding (1st workplace)	1.02 %	3.25 %	6.08 %	8.45 %	8.80 %	9.10 %
Grinding (2nd workplace)	1.07 %	3.37 %	6.22 %	8.78 %	9.14 %	9.45 %
Grinding (3rd workplace)	1.07 %	3.35 %	6.19 %	8.60 %	8.95 %	9.25 %
Grinding (4th workplace)	0.99 %	3.16 %	6.12 %	8.53 %	8.88 %	9.19 %
Painting chamber 1	0.34 %	1.29 %	2.55 %	3.66 %	3.81 %	3.94 %
Painting chamber 2	0.38 %	1.33 %	2.47 %	3.60 %	3.75 %	3.88 %
Inspection workplace	2.46 %	9.78 %	18.76 %	27.14 %	28.25 %	29.22 %
Rework workplace	0.47 %	1.69 %	3.25 %	4.64 %	4.83 %	4.99 %

In the assembly phase, the workplace utilization improved on average expectingly, because of the higher number of output units. For pre-assembly workplaces, the utilization improved on average by 9.29 %, for welding by 79.47 %, for grinding by 8.21 %, for painting chambers by 3.55 %, for inspection of subassemblies by 26.76 %, and 4.53 % for rework. In the production phase, the workplaces or machines were well balanced from the aspect of utilization. As for the assembly phase, the improvements made a utilization difference for the welding workplaces, between the first five and the last two workplaces. This difference is most noticeable for the experimental setting shown in column 4 in Table IV (small quantities batch size and interarrival time change for 10 units of final subassembly). By introducing the small quantities batch size and interarrival time change for 20 units of final subassembly (experimental setting 5) this difference was reduced for welding's 6th workplace, and with fine adjustments (experimental setting 6) also got reduced for the 7th workplace, getting the welding workplaces better balanced.

4. CONCLUSION AND FURTHER WORK

The presented optimization process helped to reduce the production cycle time and to produce the needed quantities. The advantage of this approach is the application practicality and comprehensibility of simulation-based optimization steps and that it currently does not require complex software integration for its implementation. Compared to other approaches mentioned in this paper, the main limitation of this approach was that it required several iterations for algorithm steps, which means that the process parameters settings are needed to be consulted and adjusted manually (having in mind the production planners' availability and knowledge), followed then by the simulation itself and the analysis of the results. Since the optimization represents an added step in the whole manufacturing process, this limitation can represent an obstacle because of the time needed to conduct the optimization. To overcome this limitation and to speed up the optimization, some algorithm steps can be improved.

The proposal is to improve the process technologically as much as possible, without the change of the order of algorithm steps. For the initial simulation model development and optimization goals and their performance measures setting this is not necessary (although it is possible), considering the data availability and the issues which can arise of automated simulation model generation like detailed or complex model [27], and because there is a lot of human decision which can't be carried out from an automation software side. In the parameter optimization phase, the parts grouping step can be done relatively fast, with the assumption that the routing and other necessary data are available, so there is no need for this step automation.

Following previous research papers on possible tools and workflow pipelines [28-31], for further research on the algorithm steps improvement, two things can be considered.

The first is to identify and automate the tasks which are needed for data transfer from one software to another. These tasks are ideal candidates for automation, for example, data exchange between simulation software and data analysis software. Data collection and transfer can be automated via data streaming management software, which would be a layer between simulation software and data analysis software. Further research on how to integrate this different software would be highly helpful.

The second is to improve the optimization steps. It would be necessary to improve the parameter adjustment based on the analysis of provided input parameters (simulation results), so this would mean moving from spreadsheet software to a customized solution for decision support, or to pair it with a data mining solution. Additionally, this could enable feeding the data analysis software not only with simulation results but also with real-time data from the shop floor. Further research on the possibilities of utilizing both simulated data and real-time data would be beneficial to parameter optimization from the perspective of interconnectivity between model and real process, thus enabling a better quality of insights and extending the application field of the simulation-based optimization algorithm.

REFERENCES

[1] De Sousa Junior, W. T.; Montevechi, J. A. B.; de Carvalho Miranda, R.; Campos, A. T. (2019). Discrete simulation-based optimization methods for industrial engineering problems: a systematic literature review, *Computers & Industrial Engineering*, Vol. 128, 526-540, doi:10.1016/j.cie.2018.12.073

[2] Melesse, T. Y.; di Pasquale, V.; Riemma, S. (2020). Digital twin models in industrial operations: a systematic literature review, *Procedia Manufacturing*, Vol. 42, 267-272, doi:10.1016/j.promfg.2020.02.084

[3] Liao, J.; Lin, C. (2019). Optimization and simulation of job-shop supply chain scheduling in manufacturing enterprises based on particle swarm optimization, *International Journal of Simulation Modelling*, Vol. 18, No. 1, 187-196, doi:10.2507/IJSIMM18(1)CO5

[4] Petroodi, S. E. H.; Eynaud, A. B. D.; Klement, N.; Tavakkoli-Moghaddam, R. (2019). Simulation-based optimization approach with scenario-based product sequence in a reconfigurable manufacturing system (RMS): a case study, *IFAC-PapersOnLine*, Vol. 52, No. 13, 2638-2643, doi:10.1016/j.ifacol.2019.11.605

[5] Ištoković, D.; Perinić, M.; Borić, A. (2021). Determining the minimum waiting times in a hybrid flow shop using simulation-optimization approach, *Technical Gazette*, Vol. 28, No. 2, 568-575, doi:10.17559/TV-20210216132702

[6] Istokovic, D.; Perinic, M.; Vlatkovic, M.; Brezocnik, M. (2020). Minimizing total production cost in a hybrid flow shop: a simulation-optimization approach, *International Journal of Simulation Modelling*, Vol. 19, No. 4, 559-570, doi:10.2507/IJSIMM19-4-525

[7] Jemmali, M.; Hidri, L.; Alourani, A. (2022). Two-stage hybrid flowshop scheduling problem with independent setup times, *International Journal of Simulation Modelling*, Vol. 21, No. 1, 5-16, doi:10.2507/IJSIMM21-1-577

[8] Mourtzis, D.; Vasilakopoulos, A.; Zervas, E.; Boli, N. (2019). Manufacturing system design using simulation in metal industry towards education 4.0, *Procedia Manufacturing*, Vol. 31, 155-161, doi:10.1016/j.promfg.2019.03.024

[9] Mourtzis, D.; Angelopoulos, J.; Panopoulos, N. (2021). Robust engineering for the design of resilient manufacturing systems, *Applied Sciences*, Vol. 11, No. 7, Paper 3067, 21 pages, doi:10.3390/app11073067

[10] Sankaran, V. S.; Segar, V.; Subramanian, B.; Krishna, A. (2015). Optimization of manufacturing process parameters using Arena simulation and Taguchi method, *International Journal of Mechanical Engineering and Robotics Research*, Vol. 4, No. 1, 435-444

[11] Uriarte, A. G.; Ng, A. H. C.; Zúñiga, E. R.; Moris, M. U. (2017). Improving the material flow of a manufacturing company via lean, simulation and optimization, *Proceedings of the IEEE International Conference on Industrial Engineering and Engineering Management (IEEM)*, 1245-1250, doi:10.1109/IEEM.2017.8290092

[12] Uriarte, A. G.; Ng, A. H. C.; Moris, M. U. (2018). Supporting the lean journey with simulation and optimization in the context of Industry 4.0, *Procedia Manufacturing*, Vol. 25, 586-593, doi:10.1016/j.promfg.2018.06.097

[13] Omogbai, O.; Salonitis, K. (2016). Manufacturing system lean improvement design using discrete event simulation, *Procedia CIRP*, Vol. 57, 195-200, doi:10.1016/j.procir.2016.11.034

[14] Pattanaik, L. N. (2021). Simulation optimization of manufacturing takt time for a leagile supply chain with a de-coupling point, *International Journal of Industrial Engineering and Management*, Vol. 12, No. 2, 102-114, doi:10.24867/IJIEM-2021-2-280

[15] Sabaghi, M.; Rostamzadeh, R.; Mascle, C. (2015). Kanban and value stream mapping analysis in lean manufacturing philosophy via simulation: a plastic fabrication (case study), *International Journal of Services and Operations Management*, Vol. 20, No. 1, 118-140, doi:10.1504/IJSOM.2015.065977

[16] Tanasic, Z.; Janjic, G.; Sokovic, M.; Kusar, J. (2022). Implementation of the lean concept and simulations in SMEs – a case study, *International Journal of Simulation Modelling*, Vol. 21, No. 1, 77-88, doi:10.2507/IJSIMM21-1-589
[17] Xu, J.; Huang, E.; Hsieh, L.; Lee, L. H.; Jia, Q.-S.; Chen, C.-H. (2016). Simulation optimization in the era of Industrial 4.0 and the Industrial Internet, *Journal of Simulation*, Vol. 10, No. 4, 310-320, doi:10.1057/s41273-016-0037-6
[18] De Paula Ferreira, W.; Armellini, F.; de Santa-Eulalia, L. A. (2020). Simulation in industry 4.0: a state-of-the-art review, *Computers & Industrial Engineering*, Vol. 149, Paper 106868, 17 pages, doi:10.1016/j.cie.2020.106868
[19] Debevec, M.; Simic, M.; Jovanovic, V.; Herakovic, N. (2020). Virtual factory as a useful tool for improving production processes, *Journal of Manufacturing Systems*, Vol. 57, 379-389, doi:10.1016/j.jmsy.2020.10.018
[20] Semeraro, C.; Lezoche, M.; Panetto, H.; Dassisti, M. (2021). Digital twin paradigm: a systematic literature review, *Computers in Industry*, Vol. 130, Paper 103469, 23 pages, doi:10.1016/j.compind.2021.103469
[21] Silva, J.; Silva, F. J. G.; Campilho, R. D. S. G.; Sá, J. C.; Ferreira, L. P. (2021). A model for productivity improvement on machining of components for stamping dies, *International Journal of Industrial Engineering and Management*, Vol. 12, No. 2, 85-101, doi:10.24867/IJIEM-2021-2-279
[22] Abdi, M. R.; Labib, A. (2017). RMS capacity utilisation: product family and supply chain, *International Journal of Production Research*, Vol. 55, No. 7, 1930-1956, doi:10.1080/00207543.2016.1229066
[23] Cáceres-Gelvez, S.; Arango-Serna, M. D.; Zapata-Cortés, J. A. (2022). Evaluating the performance of a cellular manufacturing system proposal for the sewing department of a sportswear manufacturing company: a simulation approach, *Journal of Applied Research and Technology*, Vol. 20, No. 1, 68-83, doi:10.22201/icat.24486736e.2022.20.1.1335
[24] Zhang, Q.; Segerstedt, A.; Tsao, Y.-C.; Liu, B. (2015). Returnable packaging management in automotive parts logistics: dedicated mode and shared mode, *International Journal of Production Economics*, Vol. 168, 234-244, doi:10.1016/j.ijpe.2015.07.002
[25] King, D. H.; Harrison, H. S. (2013). Open-source simulation software "JaamSim", *Proceedings of the Winter Simulations Conference*, 2163-2171, doi:10.1109/WSC.2013.6721593
[26] King, D. H.; Harrison, H. S. JaamSim: Leading Edge Simulation, from *https://jaamsim.com/*, accessed on 24-03-2021
[27] Lugaresi, G.; Matta, A. (2020). Generation and tuning of discrete event simulation models for manufacturing applications, *Proceedings of the Winter Simulation Conference*, 2707-2718, doi:10.1109/WSC48552.2020.9383870
[28] Ismail, A.; Truong, H.-L.; Kastner, W. (2019). Manufacturing process data analysis pipelines: a requirements analysis and survey, *Journal of Big Data*, Vol. 6, Paper 1, 26 pages, doi:10.1186/s40537-018-0162-3
[29] Sahal, R.; Breslin, J. G.; Ali, M. I. (2020). Big data and stream processing platforms for Industry 4.0 requirements mapping for a predictive maintenance use case, *Journal of Manufacturing Systems*, Vol. 54, 138-151, doi:10.1016/j.jmsy.2019.11.004
[30] Wang, N.; Li, X. J.; Nie, H. (2021). Digital production control of manufacturing workshop based on Internet of Things, *International Journal of Simulation Modelling*, Vol. 20, No. 3, 606-617, doi:10.2507/IJSIMM20-3-CO15
[31] Santos, R.; Basto, J.; Alcalá, S. G. S.; Frazzon, E.; Azevedo, A. (2019). Industrial IoT integrated with simulation – a digital twin approach to support real-time decision making, *Proceedings of the International Conference on Industrial Engineering and Operations Management*, 816-828