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A Combined Discrete Event Simulation and Factorial Design Experiment for the Scheduling Problem in a Hybrid Flow Shop

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Abstract: Production plants have always been confronted with the problem of scheduling, as this has a direct impact on production time and therefore on production costs. This is especially true in today's world, where it is necessary to produce a quality product at a low price and in a short time, while at the same time responding flexibly to customer demands. Due to the complexity and for economic reasons, testing different variants in a real production environment is insufficient and ineffective. For this reason, this paper proposes a new method that combines discrete event simulation and factorial design experiment to find the optimal schedule in hybrid flow shop. It was tested with the goal of achieving the minimum makespan. The results show that this method makes it possible to find improved solution very quickly. Compared to the original production schedule, the makespan could be reduced by 3 hours and 31 minutes which is reduction of 16.3%. The proposed methodology can be used in many discrete and process production plants.

Keywords: Discrete Event Simulation; factorial design experiment; Hybrid Flow Shop; makespan; scheduling; Tecnomatix Plant Simulation

1 INTRODUCTION

Industrial manufacturing has undergone considerable changes in recent decades. These changes affect both the scale and complexity of manufacturing and the technologies used [1, 2]. In order to be competitive, manufacturers must produce high-quality products at a low price and at the same time respond flexibly to the frequently changing needs of customers [3]. This is precisely why simulation programs are increasingly being used today to assess whether potential changes will have a positive or negative impact. A large number of successful companies and enterprises use a variety of simulation programs for planning and production management. The use of such programs makes it possible to view the entire production process at macro and micro level, whereby the simulation can be stopped and restarted at any time [4]. Among other things, testing solutions in a real environment is extremely costly, which manufacturing companies cannot afford [5]. Therefore, the use of simulation programs has proven to be an excellent tool for improving production performance [6].

To achieve the production goals, one of the main tasks is to set up a schedule for production and allocate all the necessary resources - better known as the scheduling problem. Scheduling is about finding the optimal order of execution of certain jobs within the production system under consideration, with the aim of finding an optimal solution - makespan, flow time, tardiness, manufacturing costs, and others [7].

HFS is characterized by the production of medium or large quantities of several different, technologically similar products, whereby the products move unidirectionally through the production process and are processed at more than one stage [8, 9]. Within each stage, there are one or more machines of the same type - parallel machines. On each machine only one operation can be performed simultaneously, and once the operation has been started on the machine, it can no longer be interrupted [10]. The operation of a work task can only be executed only if the previous operations on this work task have been executed [11]. Considering the real-world environment, Hybrid Flow Shop (HFS) is the preferred choice for process and discrete manufacturing companies that engage in custom manufacturing and mass customization, such as in the manufacture of automobiles, machinery, electronics, and other products [12]. The mentioned problem is an NP-hard problem and there is a growing number of scientific papers dealing with its solution. The authors have proposed various techniques, methods and algorithms to solve this type of problem. In their work, Antonova et al [13] proposed an imitation and heuristic method for solving the assigned scheduling problem in a real project company. They use the proposed method to find a schedule that satisfies the time and resource constraints and minimizes the subcontracted resources cost. Janeš et al. use a modified steady-state Genetic Algorithm (GA) to solve batch sizing and scheduling problems with limited buffers in HFS [14]. To find an optimal schedule with the goal of minimizing production costs, Borojević et al. used an integrated CAD/CAPP platform based on elementary machining features and the GA [15]. To solve the scheduling problem in HFS, Rashid & Mu'tasim [16] used an improved Tiki-Taka algorithm which is a novel sport-inspired algorithm based on a football playing style.

Nowadays, one of the most commonly used tools is Discrete Event Simulation (DES), as it allows the creation of a digital model of the observed production system from a real environment and simple modifications to the model without disturbing the operation of the real production system. It also allows the evaluation of the operational characteristics of the existing production system and the prediction of the operational characteristics of the planned production system, where alternative solutions can be compared [2].

With DES, however, it is not possible to find an optimal or sufficiently good solution. Especially not for scheduling problem, which is considered in this paper. For this reason, the combination of DES with other optimization tools is recognized as a promising solution. The authors Ištoković et al. [17] proposed a combination of DES with a GA to find the minimum production cost. The simulation-optimization approach was also applied by Klanke & Engell [18], who used a tailored Evolutionary Algorithm (EA) as an optimizer and a commercial DES as a schedule builder for solving batching and scheduling problem. Although in these approaches better solutions were obtained, but both approaches require a relatively large amount of real-time to find a sufficiently good solution.

Accordingly, this paper proposes a new method based on the application of the probability of occurrence of a work task, i.e. products in the process, combining DES and factorial design experiment with the aim of finding a improved solution in a small amount of real-time. The method is tested for the case of a minimum makespan. So far, several researchers have applied a combination of DES and factorial design experiment [19-22], but not for the case of solving the scheduling problem in a HFS.

The rest of the paper is organised as follows. Section 2 contains a detailed description of the proposed new method based on the probability of product entry into the process for fixed production quantities, combining DES and factorial design experiment to find an improved solution. The results of the conducted research are presented in Section 3, and finally, concluding considerations and suggestions for future research are made in Section 4.

2 METHODOLOGY

2.1 Notation

This paper considers the scheduling problem in a HFS, where the goal is to determine the optimal schedule to complete the production of a given quantity of products as early as possible. It is important that the result - the improved schedule - is achieved in a short period of time.

The parameters used in this paper are as follows:

- N set of jobs/products,
- S set of stages,
- M_i set of identical parallel machines at each stage i,
- j job/product type ($j = 1, 2, \dots , n$),
- i stage/production phase ($i = 1, 2, \dots , s$),
- k machine ($k = 1, 2, \dots , m$),
- o_{ij} operation of product j at stage i,
- p_{ijk} processing time of product j at stage i on machine k,
- q_j production quantity of product j,

2.2 Problem Description

In this paper, three different types of products are produced in the plant (labelled A, B, and C), and the production quantity of each product to be produced is shown in Tab. 1.

Table 1 Types and quantity of products

j	A	B	C
q_j	40	50	30

The observed HFS consists of five stages, within which there are one or more identical parallel machines. More precisely, there is one machine in the first stage, two identical machines in the second stage, three identical machines in the third stage, one machine in the fourth stage and two identical machines in the fifth stage. The number, sequence of operations and processing times for each of the three products listed are given in Tab. 2. Each operation has a fixed duration and is given in minutes. The values given and the proposed production process were taken from a real-world production plant that manufactures parts for industrial machinery.

Table 2 Sequence of operations and processing times

o_{ij}	A	B	C	M_i
1	5	-	5	1
2	8	7	8.5	2
3	-	10	10.5	3
4	18	-	11.5	1
5	-	5	5	2

In this case, the products move unidirectionally through the production process. The availability of the machines is assumed to be 100%, i.e. failures are not taken into account. The transportation between the workplaces (machines) as well as the transportation from the storage of raw materials (SRM) and the transportation to the storage of finished products (SFP) are neglected. The time needed for the setup of the workplaces was also neglected. Additional conditions are that only one operation can be carried out on each machine, and once it has been started, it must not be interrupted. The sequence of operations must be adhered to. An operation on a product can only be carried out until the previous operations have been carried out on the product.

2.3 Simulation Model

The simulation model for the observed HFS was created using Tecnomatix Plant Simulation software version 14.1. This software enables the modeling, simulation, analysis, visualization, and optimization of production systems and processes. It has proven to be very useful and is used by numerous authors in their research to solve production problems [23-25].

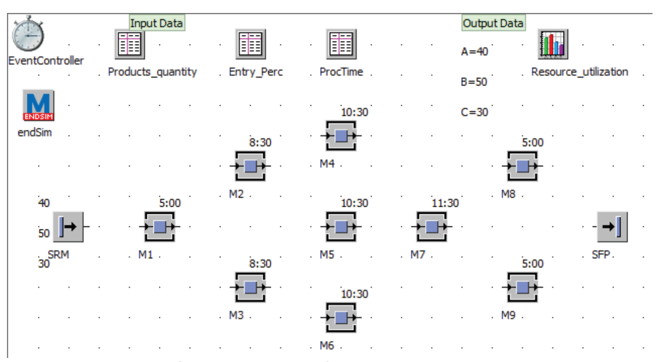

Figure 1 Simulation model of observed production process

The layout of the simulation model with all the necessary elements describing the observed production process is shown in Fig. 1. Every simulation model must be verified and validated to ensure that high-quality and accurate solutions are achieved. According to [26], verification shows whether the created simulation model and all its elements work correctly, while validation shows a satisfactory accuracy range that is consistent with the intended application [27]. For this reason, the necessary elements were included in this simulation model in order to enable simple verification and validation of the simulation model.

The products are initially produced in a cycle, i.e. they are produced in such a way that the entire production quantity of product A is produced first, then the entire production quantity of product B and then the entire production quantity of product C. In such a process, the completion time for the production of these products is 21:33:00. The specified time format is hours:minutes:seconds [hh:mm:ss]. This production strategy was chosen as a starting point because it is the easiest to apply in a real environment. Based on the data obtained from the simulation model, an initial schedule can be seen in Fig. 2.

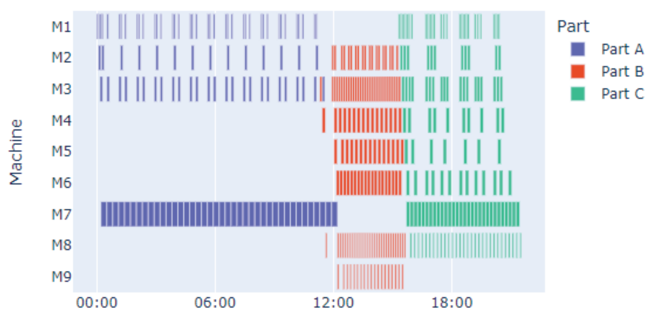

Figure 2 Gantt chart for initial schedule

2.4 Description of the Methodology with Probabilities

A production in which the products are produced in a cycle does not lead to an optimal solution. Therefore, this paper proposes a new method for determining the optimal order of entry of each product into the process based on the probability of each product entering into the process for fixed production quantities. The aim is to minimise the makespan.

Each product type is assigned a specific integer value pn_j according to Eq. (1).

$$pn_j \in [0, 100]. \tag{1}$$

The probability of entry of a certain product type pp_j is then determined according to Eq. (2) as the ratio of the allocation of the pn_j value to the total sum of the allocation values of all product types. In this way, a large search space, i.e. a large number of possible solutions is made possible.

$$pp_j = \frac{pn_j}{pn_1 + pn_2 + \cdots + pn_n}. \tag{2}$$

As an example of a simple case let us assume that the values of pn_j for the three products mentioned (A, B and C) are the same, i.e. $pn_A = pn_B = pn_C = 20$. In this case, the sum of these values is 20 + 20 + 20 = 60. By calculating according to Eq. (2), we obtain the probabilities for product entry of each product, which are 20/60 = 0.33 or 33%. The given value shows that product A (in this case also B and C) enters the process i.e. it is created at the Storage of Raw Materials (SRM) with a probability of 33%.

Since there is a large search space to find the optimal solution, the optimal probability of entry for a certain product type, the factorial design experiment is applied to find a sufficiently good solution.

2.5 Description of the Factorial Design Experiment and Response Surface Methodology

Factorial experiments are designed in such a way that two or more factors have discrete possible values (levels) so that the effect of each factor on the response value can be studied. It is often used in conjunction with Response Surface Methodology (RSM), which was originally developed to improve manufacturing processes in the chemical industry by optimizing chemical reactions, which was achieved by conducting experiments with different factors. The methodology can be used to optimize any response that is affected by the level of one or more factors. Once the response surface is obtained, it can help to identify the combination of factors considered that can maximize or minimize the target value [28].

In this paper, the specific integer value for products A, B and C were considered in 4 levels, i.e. with values of 20, 40, 60 and 80. This resulted in 4-level 3 factor full factorial design used. The objective was to minimize the production completion time - makespan. Considering the fast execution of the simulations, a full factorial experiment was considered, where the simulation was performed with all possible combinations of stages, leading to 64 results.

The response surface was approximated by a polynomial regression model. The Python module scikit-learn version 0.21.3. was used to implement the regression models. The polynomial orders considered were the second, third and fourth. To validate further the proposed methodology, two additional scenarios with different product quantities were considered (see Tab. 3). In the additional scenarios, the initial production schedule was the same as in the first scenario (first the entire production quantity of product A is produced, then of product B and then of product C).

Table 3 Cases examined for the factorial design experiment with type and quantity of products

Scenario	A	B	C
1	40	50	30
2	175	200	300
3	200	125	145

3 RESULTS
3.1 Simulation Results

The best results obtained with the full factorial approach are shown in Tab. 4, indicating the times and parameters used for the simulation. It can be seen that the full factorial exploration achieves better results in all scenarios.

Table 4 Results of full factorial design experiment

Scenario	1	2	3
Base result [dd:hh:mm:ss]	21:33:00	5:13:53:00	4:06:50:00
Improved result [dd:hh:mm:ss]	18:02:00	4:23:54:00	3:22:01:00
pn_A	40	20/40/40/60/60	60/60/80/80
pn_B	60	40/60/80/80/80	40/80/60/80
pn_C	20	40/80/80/40/80	40/40/60/60
Time reduction [dd:hh:mm:ss]	3:31:00	13:59:00	8:49:00

It should be noted that different combinations of specific integer values pn_j lead to the same results for scenarios 2 and 3. For scenario 2, for example, the two combinations [20,40,40] and [40,60,80], where the numbers are specific integer numbers for product *A*, *B* and *C* respectively, lead to the same production time, i.e. 4:23:54:00. This is due to characteristics of probability calculation, described in more detail in subsection 2.4. Therefore, some of the combinations of variables lead to the same or similar set of parameters.

3.2 Response Surface - Regression Models

For the Scenario 1, the response surfaces for second-, third- and fourth-order regression polynomials are shown in Fig. 3. The figures show areas with minimum values that should be examined more closely in order to possibly obtain better solutions.

Apart from the differences in the shape of the response surface, which can be seen in the figures, the errors of the regression model (Eq. (3)) are calculated as root mean squared error:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(y_i - \hat{y}_i\right)^2}. \tag{3}$$

Where y_i is the actual time of production obtained from the simulation model, $\hat{y}_i$ is the estimated time of production obtained from the regression model, and n is the number of observations, which in this case is 64. The results are shown in Tab. 5. It can be observed that as the polynomial degree increases, the root mean squared error decreases in all cases, which is expected, since greater order polynomial models better fit the data. However, it should be noted that a smaller root mean squared error does not mean a better approximation to the response surface in the optimum area. Additionally, higher order polynomials can lead to overfitting, so the polynomial degree should be chosen according to the problem under consideration.

Table 5 Root mean squared error of regression polynomials

Scenario	Polynomial degree		
	2	3	4
1	19 min	12 min	9 min
2	15 min	13 min	12 min
3	10 min	7 min	6 min

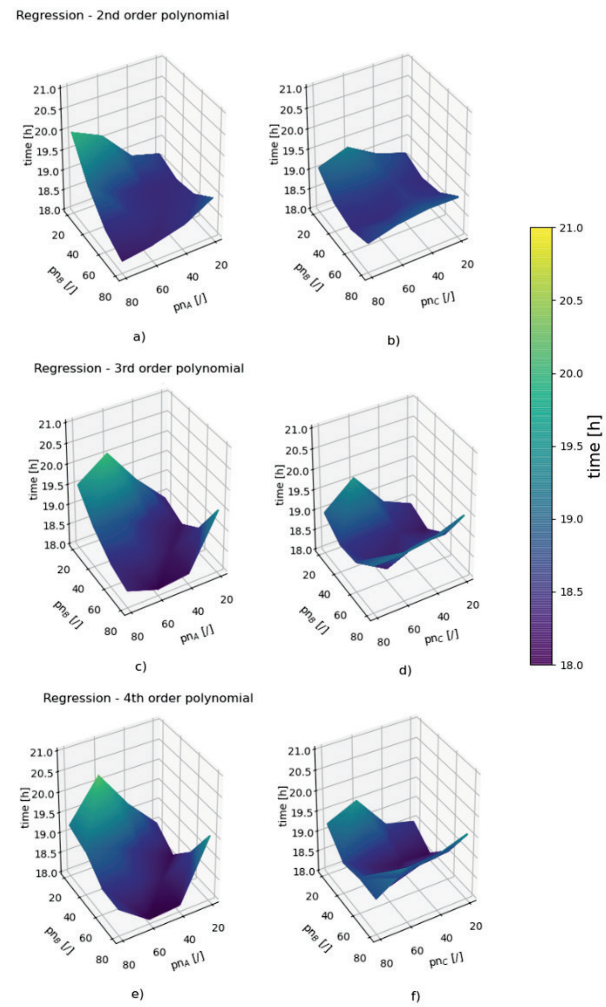

Figure 3 Response surfaces for regression polynomials for: a), b) 2nd order polynomial, c), d) 3rd order polynomial, and e), f) 4th order polynomial

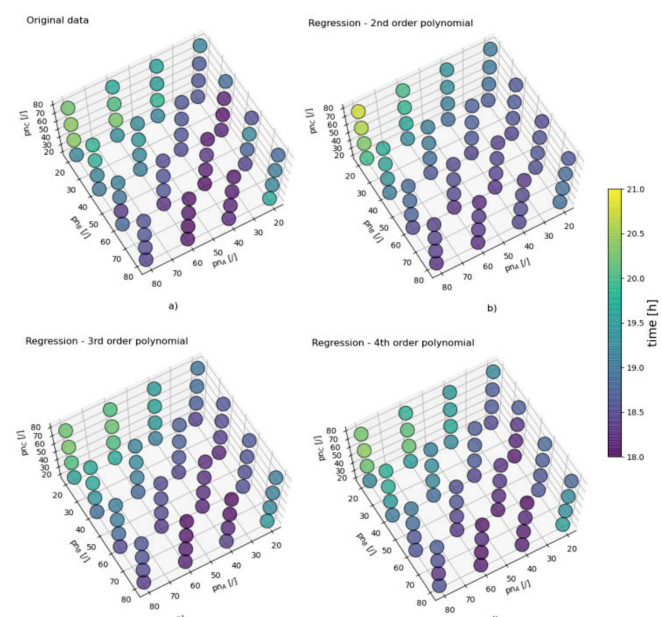

Figure 4 Scatterplot for Scenario 1: Full factorial points for: a) original data, b) 2nd order polynomial, c) 3rd order polynomial, d) 4th order polynomial. The X, Y and Z coordinates represent the specific integer values pn_j. Color represents makespan.

For a better visual representation of the differences in polynomial degree, a scatter plot of the data points is shown in Fig. 4. The colors of the markers indicate the time of the simulation.

3.3 Improved Schedule

Based on the optimal results obtained, a Gantt chart was created for scenario 1, which is shown in Fig. 5 and shows the schedule for the use of production resources (in this case the machines).

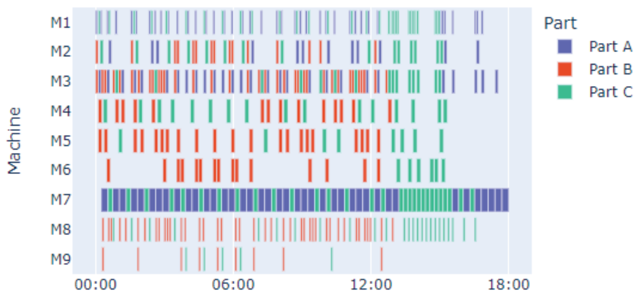

Figure 5 Gantt chart for improved schedule

Compared to Fig. 2, it can be seen that there is no clear pattern for the product entrance in the production process. It can also be observed that the utilisation of the machines is improved, especially for machines M4, M5, M6, M8 and M9, which are mostly not used in the first 12 hours in the initial scenario. It is noted that such a Gantt chart is difficult for the operator to plan without the use of computational strategies such as those used in this paper, as there is no clear pattern for the product entrance. As a result, the production time could be reduced considerably.

4 DISCUSSIONS AND CONCLUSION

One of the most important tasks in ensuring the competitiveness of production companies is to determine production schedules. In contrast to previous achievements in this field, this paper proposes a new method based on the probability of a product entering the production process for fixed production quantities. The proposed method combines DES and factorial design experiment to find the improved (good enough) schedule in HFS with the aim of determining the minimum makespan in this case.

The proposed methodology was successfully applied to the cases investigated. A shorter makespan was achieved in all scenarios compared to the base scenario. In particular, for the observed Scenario 1, the makespan was reduced by 3 hours and 31 minutes, which corresponds to a reduction of 16.3% compared to the original schedule. The results also show that the proposed method provides improved solutions very quickly.

Based on the obtained results of full factorial design response surface was prepared indicating areas for further exploration for obtaining better results. Therefore, considering that only 64 points were used, an optimization procedure of the response surface will be performed in future work to achieve further improvement of results. This can be achieved by increasing the number of levels for the factors or by additional evaluations close to the current best solutions. It should be noted that with longer times required to simulate the production process, the full factorial design could require a significant amount of time. Therefore, a fractional factorial design can also be investigated in future work. This can be particularly advantageous when a quick response to changes in the process is required.

The strategy proposed in this paper was applied to a scenario with 3 parts and 9 machines. In future work, the applicability to scenarios with a larger number of parts will be investigated. It can be assumed that a higher complexity of the problem will not affect the efficiency of the method. Therefore, these studies will help to confirm that the proposed strategies can be used efficiently under conditions that require high production flexibility and allow a quick response to new orders. This will increase the efficiency of production and increase competitiveness, which is becoming increasingly important due to the need for scalability and the complexity of industrial production.

It must be noted that some simplifications have been made in this paper, e.g. the setup of the machines was neglected. When considering the flexibility of the proposed methodology for new orders, this should also be taken into account in order to obtain realistic results. As failures were not considered, it would also be interesting to investigate how failures on different machines could affect the production process and how the proposed strategy could be superior to standard procedures in this case. Another uncertainty that can be considered is the inclusion of the possibility of a defect in the raw material or semi-finished product, which can also cause a stoppage in production. This can be simulated by including these uncertainties in the simulation model, as the software itself allows for this and in this way comes even closer to reality. In this paper, a worker or a robot is not considered for the manipulation of the workpiece/part at the workplace, which should also be considered in future research, since the effective working time of the worker is less than the effective working time of the robot (physiological needs, fatigue, motivation, etc.).

Considering the simplifications mentioned above, which include neglecting transportation between machines, transportation from the SRM and transportation to the SFP, it should be noted that the regression polynomial can be prepared not only with simulated points but with real data from the production process. Moreover, the regression polynomial was used as a simple strategy to investigate the feasibility of the proposed approach. Some other machine learning models could be used to improve the efficiency of the proposed methodology.

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