




Article

Multi-Objective Optimization of Production Objectives Based on Surrogate Model

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Abstract: The article addresses an approximate solution to the multi-objective optimization problem for a black-box function of a manufacturing system. We employ the surrogate of the discrete-event simulation model of a batch production system in an analytical form. Integration of simulation, Design of Experiments methods, and Weighted Sum and Weighted Product multi-objective methods are used in an arrangement of a priori defined preferences to find a solution near the Pareto optimal solution in a criterion space. We compare the results obtained through the analytical approach to the outcomes of simulation-based optimization. The observed results indicate a possibility to apply the suitable analytical model for quickly finding the acceptable approximate solution close to the Pareto optimal front.

Keywords: multi-objective optimization; metamodel; surrogate model; manufacturing system; simulation-based optimization

1. Introduction

Every day, we face moments of decision-making where we must take into account more aspects at the same time. We need to consider more than one goal simultaneously, while some of them are often contradictory. The result is finding a solution that has compromise. We can find similar situations in many domains, such as engineering, business, or manufacturing. In production control, one can typically find many frequently appearing optimization tasks for different levels of production control, whether in scheduling operations [1,2], logistics [3–5], or optimizing production objectives [6]. Each of these problems internally includes the necessity of considering different features of a system's performance. This type of problem is commonly referred to as a multi-objective or vector optimization problem (MOOP) [7]. In contrast to a single objective optimization, to solve it is generally not trivial, because there is no unique optimal solution but rather a set of compromise solutions [8]. Therefore, it demands applying multi-objective optimization methods to find acceptable optimal solutions.

A direct analytical approach for finding MOOP solutions can fail in the optimization of real-world systems due to difficulties caused by their performance complexity. In general, none or weakly analytically expressed information exists concerning the system dynamics of a relationship between a cause and a consequence. It means that we do not know the precise analytical relation between system inputs and outputs in a form of inputs–outputs transformation. Thus, the effect of decisions or applying specific design scenarios cannot be determined by direct calculation, but it must be studied by applying other methods, such as simulation or simulation-based optimization [9,10].

Both methods are important in the determination of system outputs or objective functions values, respectively. Computer simulation represents one of the most advanced and useful tools in the analysis

of complex systems. It shows the true system behavior and offers a prediction of a future performance. Consequences of decisions and applying design scenarios in relation to the performance evaluation can be tested easily. Simulation-based optimization employs a simulation approach to evaluate unknown values of objective function during an optimization process. The method is time-consuming when exploring a large design space, mainly due to its high dimensionality.

Due to the complexity of manufacturing systems, and hand in hand with computational capabilities, one of the approaches to find solutions of an MOOP in this environment can be based on dealing with an explored system as a black box [11,12]. The black-box function represents mapping the design space to the space of responses as system outputs. Its direct application in the optimization via a method of simulation-based optimization is mostly computationally expensive [13]. Many optimization strategies, including metaheuristics and simulation-based techniques, are mentioned in survey by Liu et al. [14]. Despite the solutions that result from any of these methods most likely being suboptimal, metaheuristics perform well in practice [8], even if they do not guarantee identifying a Pareto optimal solution.

The increasing requests for an automation of the manufacturing processes control demands solving an MOOP as fast as possible. To offer the suitable solution in a very short time is in contrast to the time-consuming NP-hard problem (NP stands for Non-deterministic Polynomial) solving, which constrained MOOP solving mostly represents with no doubt. The algorithmic complexity $O(k^n)$ of NP-hard problems is given by both the small velocity of finding and verifying the solution. They belong to the category of problems that cannot be generally solved in polynomial time but exponential time that depends on input size n . As an alternative of metaheuristics, the way to deal with the MOOP can be through finding the adequate surrogate model of a costly evaluated function, which allows solving an MOOP with significant speed-up [13,15]. The challenge is to find a suitable compromise between calculation acceleration and model precision [16].

As an example of an application of an idea of metamodeling-based optimization in manufacturing control, Azadeh and Maghsoudi [17] employ a simulated Design of Experiments (DoE) and metaheuristic method Tabu Search in a single objective optimization. They conclude that the procedure is suitable for performance optimization in all types of discrete production systems. Conceptually inspired by this case study, in our work, we try to overcome the problem of a long-lasting process of MOOP solving connected to simulation-based optimization and to offer an alternative in which an approximate analytical approach is implemented. The intention of this work was to verify the possibility of finding approximate MOOP solutions that are close to Pareto optimal ones when applying a surrogate model of a simulation model for a batch production system. After derivation of the surrogate model for system input–output transformation in an analytical form and its employment in MOOP solving, we expected a substantial reduction of calculation time from several hours to minutes compared to simulation-based optimization with only an insignificant loss of solutions accuracy.

In this study, we adopted a scalarization technique with a priori defined preferences in the connection with simulation-based and surrogate-based multi-objective optimization. We employed the discrete-event simulation model of a batch production system to allow observing and predicting the system behavior and its response with respect to the external input parameters changes. It was a data source for acquiring the simulation outputs as further inputs to the DoE performance. It also served as an optimization model after completing it by the multi-objective function and by required constraints for simulation-based optimization. We used it for verification of the results of the surrogate-based optimization experiments.

The reminder of the paper is structured as follows. In Section 2, a definition of the multi-objective optimization problem, modeling of surrogates, and applications related to an integration of both approaches are presented. Section 3 introduces the steps of the proposed procedure for approximate solving of the MOOP when employing surrogate models in simultaneous optimizing production objectives. In Sections 4 and 5, we present the obtained results and discuss the limitations. Section 6 summarizes the work results and indicates a future research direction.

2. Background of Multi-Objective Optimization Based on a Surrogate Model

2.1. Multi-Objective Optimization Problem (MOOP)

In general, finding the solution of an MOOP can be presented as a procedure of simultaneous optimization of a set of k individual objective functions under the constraints set. It can be defined in form given in Equation (1) referring to Marler and Arora [7]:

$$\begin{aligned} &\text{Minimize } x \in D && F(x) = [F_1(x), F_2(x), \dots, F_k(x)]^T; k \geq 2 \\ &\text{subject to} && g_s(x) \leq 0, s = 1, 2, \dots, m; m \geq 0, h_l(x) = 0, l = 1, 2, \dots, r; r \geq 0. \end{aligned} \quad (1)$$

The vector $x \in D$, where the set D is the feasible region in the design space, is constrained by its lower and upper limits $x_L \leq x \leq x_U$. The vector $F(x) \in E_k$ is the vector of objective functions $F_i(x): E_n \rightarrow E_1$ in feasible objective space Z , $Z \subset E_k$. Thus, Z is the forward image of D under the mapping F [8]. The value m defines the number of inequalities, and r defines the number of equalities for the constrained problem. If the objectives of F_i are contradictory, there does not exist only one single optimal solution as a MOOP-solving result. This process leads to the set of tradeoffs that are completely equivalent in a mathematical sense.

Due to the obvious nonexistence of absolute ordering solutions in the space of objective functions [18], an expert in the role of decision-maker is important as a support for the determination of the most appropriate solution [7]. In general, multi-objective methods can be principally characterized with the respect to the involving decision-maker (DM) preferences, which play a significant role in the selection of an appropriate solution. The a priori defined preferences approach provides one single optimal solution dependent on the parameters specified by the DM. On the contrary, a posteriori defined preferences methods or interactive methods allow generating a set of many optimal solutions that are offered to the DM to select the most suitable one or influence the future direction of the optimization process, respectively [7].

One of the broadly accepted concepts of identifying the optimal solution of an MOOP is an idea of Pareto optimality based on an idea of dominance in the sense of establishing the partial order of solutions. Yoshimura [19] characterizes the Pareto optimum solutions set as a set of such feasible solutions in the objective (criterion) space, where no other feasible solutions for each of them exist that will yield an improvement in one objective without causing worsening in at least one other objective. All solutions in the objective space, which have the property of Pareto optimality mentioned above, are called nondominated solutions, and other solutions in objective space are dominated by them. For precise definitions of properties of dominance and Pareto optimality, we refer to [15].

All Pareto optimal solutions form a so-called Pareto front in an objective space [15,16]. From the geometric point of view, the Pareto front represents a hypersurface in a k -dimensional space of objective functions where all nondominated solutions are located. In case of a high-dimensional design space, the hypersurface can have a very complicated structure [8]. Referring to Ehrgott [20], the pre-images of the nondominated outcomes are called efficient solutions located in design space.

The concept of Pareto optimality implemented in a method called Pareto ranking is often combined in some modifications with evolutionary algorithms [15] to increase the effectiveness of the computation of the entire set of Pareto optimal solutions.

An alternative for defining a partial order in objective space can be found in decomposition methods [8]. It is a different but very natural and therefore a widely spread approach to handle with the MOOP solving by its decomposition to a set of single-objective optimization problems. This strategy transforms a complex multi-objective problem in a set of simple subproblems.

Decomposition methods utilize a scalarizing parametric function to aggregate all the objectives into a single scalar objective function [8]. Different setting weight vectors and other parameters relating to the individual functions lead to yielding different optimal points belonging to a Pareto front. For the simple scalarization through the Weighted Sum Method (WSM) under an assumption of the convex

constraints, it is proved that the solution is Pareto optimal if the value of the corresponding scalar multi-objective function is minimal [7]. The known disadvantage of this method can be easily explained by the geometry point of view. A scalar multi-objective function is expressed as a linear combination of individual objective functions; therefore, it offers the capability of reaching the Pareto optimal solutions only in the convex part of the Pareto front.

2.2. Modeling of Surrogates and Their Application in a Multi-Objective Optimization

Metamodeling or surrogate modeling (through the following text) is a technique for the construction of “a model of the model” or “surrogates” to cover the essential features of the input–output system behavior [16]. It approximates the black-box function analytically or generates a new model with better properties for further computation.

We can find plenty of works related to this field, focusing on optimization via metamodeling. Peitz and Dellnitz [16] give an extensive survey of different types of surrogate models used for implementation in the objective function. Geometric models such as Response Surface Models generated by Response Surface Methodology (RSM) within the Design of Experiments technique, Radial Basis Function (RBF) models, statistical models such as Kriging or Gauss regression, and models based on Machine Learning methods—Artificial Neural Networks (ANN) or Support Vector Machines (SVM)—are among the most widespread. The authors also provide an overview of works when multi-objective optimization (MOO) and metamodeling are combined. Ky et al. [11] discuss the most popular surrogate models being used in engineering designs suitable also for black-box optimization and the difficulties related to their application. They mention that polynomial models that are well-studied and employed in trust-region methods to provide approximation of the true function in local areas are unsuitable as global models for highly nonlinear multidimensional functions. The authors introduce models that are better performed in that sense, such as RBF and Kriging.

Knowles and Nakayama [21] and Voutchkov and Keane [22] particularly focus on metamodeling in multi-objective optimization. Zakerifar et al. [23] pay attention to Kriging metamodeling in multi-objective simulation optimization. In a survey of Tabatabaei and Hakanen [12], the authors introduce non-nature inspired methods for handling computationally expensive multi-objective optimization problems using surrogates. As for polynomial modeling, Barton et al. [24] analyze the quality of fits in case of applying first- and second-order polynomials and other classes of metamodels in metamodel-based simulation optimization from the local and global fit point of view.

Regarding utilizing the surrogate-based optimization methods in engineering applications of real-world problems, one can find them mainly in the field of design of systems or product properties. Pillai et al. [25] suggest a multi-objective optimization framework for offshore renewable energy mooring systems applying a random forest-based surrogate model coupled to a genetic algorithm. Park et al. [26] compare the predictive cyclone models generated by response surface methodology, back propagation neural network, and group method of data-handling networks and apply them in multi-objective optimization of the cyclone separation performance via genetic algorithm, too. Chugh et al. [27] compare the multi-objective optimization of an air intake ventilation system utilizing an evolutionary algorithm with and without a surrogate.

In particular, in the domain of designing manufacturing processes, the multi-objective optimization via metamodels coupled to simulation for machining and turning processes, respectively, is applied e.g., in Amouzgar et al. [28] or Amouzgar et al. [29]. For the optimization of a friction-drilling process, Bustillo et al. [30] describe a novel strategy for real industrial conditions based on Adaboost ensembles. Regarding the results, this prediction model provided the highest accuracy and was more easily optimized than models that resulted from other machine learning techniques.

In relation to the manufacturing systems control, when the optimization of production objectives had been solved, we can observe a predominance of applying heuristic approaches, mainly evolutionary algorithms in the recent works. Um et al. [31] presented the optimization problem of three production criteria: congestion, vehicle utilization, and the throughput via multi-objective nonlinear programming

and simulation-based optimization using an Evolution Strategy for a flexible manufacturing system with an automated guided vehicle system. Azadeh and Maghsoudi [17] suggested a robust procedure for the optimization of discrete production systems employing an integration of computer simulation, DoE, and Tabu search, and applied it in the case study for a large steelmaking workshop. Lughofer et al. [32] propose an approach for the automated optimization of process parameters in manufacturing systems to automatically compensate possible downtrends in product quality using static predictive mappings and dynamic forecast models as surrogates within the evolutionary optimization process. As for RSM techniques, Durieux and Pierreval [33] deal with regression metamodels applied in the design of an automated manufacturing system. For getting a wide overview of applications in the manufacturing system operations area, please see Liu et al. [14].

2.3. Response Surface Models

Design of experiments within its techniques offers the possibility to generate and optimize regression models through many experimental designs. Particularly, one very known and widely used RSM methodology concerns mostly fitting and optimizing quadratic models. They are constructed as the approximation given by Equation (2) for the second-order model, referring e.g., to Khuri and Cornell [34], where β_0 , β_i ($i = 1, 2, \dots, k$) and β_{ii} , β_{ij} ($i = 1, 2, \dots, k; j = 1, 2, \dots, k$) are unknown regression coefficients, x_i , x_j are input variables that influence the response y , and ε denotes a random error (or a noise) observed in y .

$$y = \beta_0 + \sum_{i=1}^k \beta_i x_i + \sum_{i=1}^k \beta_{ii} x_i^2 + \sum_{i=1}^{k-1} \sum_{j=2}^k \beta_{ij} x_i x_j + \varepsilon, \quad i < j \quad (2)$$

Box–Behnken Design (BBD) is used to build a quadratic model based on such an experimental structure in which we observe the responses at the midpoints of the edges of the experimental space [35]. It does not ensure runs at the extreme combinations of all the factors. This disadvantage is compensated by having better prediction precision in the center of the experimental space. It requires at least three factors, and the effect of each of them is tested on three levels.

Face-Centered Design (FCD) represents a special case of a variety of Central Composite Designs (CCDs). CCDs are based on a two-level screening factorial design, which is augmented with center and axial points to fit quadratic models [35]. Regular CCDs have five levels for each factor. The adaptation by choosing an axial distance $\alpha = \pm 1$ produces a Face-Centered, Central Composite Design with three levels per factor. The added axial points lay at the center of each face of the factorial space. FCD design is cuboidal rather than rotatable, which is the supposition for better prediction ability in the corners of the selected experimental space. We applied BBD and FCD designs for the construction of metamodel of a vector function of production goals within this study.

3. The Proposed Multi-Optimization Procedure Based on a Surrogate Model Implemented in Production Control

The designed procedure of surrogate-based MOOP solving is introduced in this section. We illustrate its application in a production environment. Firstly, the method of derivation of the surrogate models for the selected production goals of the batch manufacturing system via the integration of the simulation and DoE method is described. Secondly, we show how the best derived analytical models are applied in objective functions of MOOP solving to find such effective input system parameters that ensure the desired values of production objectives.

3.1. Procedure of Surrogate-Based MOOP Solving

The scheme in Figure 1 illustrates the procedure of a metamodel implementation to the MOOP solving in a production environment. Vector \vec{X} represents system inputs that will be transformed

to outputs \vec{Y} . The model structure and its configuration affect the system performance. Thus, mapping input parameters (production system loading) to outputs—production objectives, such as costs, flow time, or product quantities can be observed. Due to the fact that the direct analytical expression of this mapping is unknown, we consider the simulation model of a production system as a black box and the mapping of inputs to outputs as a black-box transformation. All the information about it can be gained from the simulation. The simulation model of a production system (production system black-box in Figure 1) serves as a data source for building the surrogate model instead of a black-box function of the underlying simulation model. Simulation experiments need to consider the design of the experimental layout originated from DoE when evaluating the production objectives as outputs of the simulation runs. Once the production objectives have been evaluated, DoE adopts the observed production goals as responses \vec{Y} according to the suggested design of the planned experiment. The derived regression models (production system metamodel in Figure 1) estimate the values of production goals \vec{Y} . These regression models by means of individual objective functions represent metamodels as analytically expressed transformations of inputs $\vec{X} \rightarrow \vec{Y}$ for the selected simulation model of a production system.

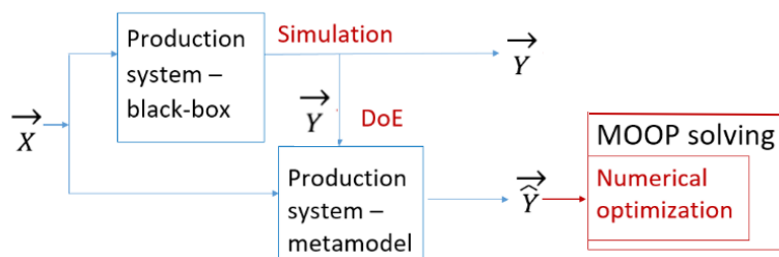


Figure 1. Scheme of the implementation of metamodel to the multi-objective or vector optimization problem (MOOP) solving.

The optimization of production means to find the effective configuration of input parameters for the black-box function to ensure the desired production performance. Therefore, metamodels for production objectives are incorporated into the scalar multi-objective function in the next step. It is subsequently minimized under specified constraints with respect to a priori defined preferences required by the selected MOO methods.

3.2. Simulation Model of Production System

The modeled production system was adapted from the work of Vazan et al. [36]. It represented a job shop-type batch production system producing two different products, P1 and P2, with eight workstations using automated parallel working machines. Three of them demanded operators to set up for processing both products. Each of these products was finishing independently at the final phase of manufacturing. We considered all internal model parameters, such as the operation times for machines, setup times and costs for operators, machine setups, and storage as fixed; therefore, the simulation model was fully deterministic. It was built in a simulator Witness Horizon version 22 by Lanner Group Limited, Houston, TX, USA. We used it to obtain values of production objectives and validate the results of numerical calculation.

3.3. Simulation Experiments

For all experiments performed on the simulation model in the Witness Horizon simulator (Lanner Group Limited, Houston, TX, USA), the inputs of the black-box function of the production system were four external input parameters—a lot size and an input arrival time for both manufacturing products. They represented loading the system. The design space was constrained by the lower and

upper bounds between values 2 and 10 pcs for the lot size, and between 5 and 50 min for the supply arrival time for both products. The system outputs were four selected production objectives—a total number of products, an average flow time, an average machine utilization, and the average costs per part unit. The simulation experiments lasted 1440 min with a 100 min warm-up period. Each of the experimental designs for the BBD and FCD-type demanded the simulation of 25 scenarios according to the experimental schemes in Figures 2 and 3, respectively.

Run	Factor 1 A:LotSizeV1 pcs	Factor 2 B:LotSizeV2 pcs	Factor 3 C:IATV1 min	Factor 4 D:IATV2 min	Response 1 Flow time min	Response 2 costs per unit €	Response 3 machine utilization %	Response 4 number of products pcs
1	10	6	5,0	27,5	714,513	62,928	81,786	283
2	10	6	27,5	50,0	403,803	14,171	68,579	283
3	10	10	27,5	27,5	589,139	20,182	90,322	283
4	6	6	5,0	5,0	785,186	87,108	94,492	286
5	2	6	50,0	27,5	258,037	9,588	37,249	201
6	2	6	5,0	27,5	524,392	16,919	79,501	287
7	6	10	27,5	50,0	456,962	10,979	60,976	287
8	6	6	27,5	27,5	458,097	11,303	62,862	287
9	10	6	50,0	27,5	463,378	11,180	60,498	283
10	10	6	27,5	5,0	690,206	54,080	91,277	283
11	2	10	27,5	27,5	322,905	13,763	56,371	247
12	2	6	27,5	50,0	135,447	6,643	34,051	248
13	2	2	27,5	27,5	53,586	6,820	27,312	210
14	6	10	50,0	27,5	403,500	12,822	64,067	287
15	6	10	5,0	27,5	677,994	53,676	94,154	287
16	6	6	50,0	50,0	216,629	7,000	41,862	287
17	6	6	5,0	50,0	493,000	47,816	72,683	287
18	6	2	27,5	5,0	526,588	16,535	76,585	287
19	2	6	27,5	5,0	390,367	55,582	64,272	248
20	6	2	50,0	27,5	137,059	6,818	35,120	249
21	6	6	50,0	5,0	471,493	49,012	71,263	286
22	6	10	27,5	5,0	706,252	66,049	80,068	285
23	6	2	27,5	50,0	258,060	10,446	40,769	202
24	6	2	5,0	27,5	414,562	54,236	65,986	249
25	10	2	27,5	27,5	325,740	15,329	62,018	246

Figure 2. Box–Behnken Design (BBD) layout defined in actual factors values. The responses in the red box are obtained from experiments on the simulation model.

Run	Factor 1 A:LotSizeV1 pcs	Factor 2 B:LotSizeV2 pcs	Factor 3 C:IATV1 min	Factor 4 D:IATV2 min	Response 1 flow time min	Response 2 costs per unit €	Response 3 machine utilization %	Response 4 number of products pcs
1	2	2	5,0	50,0	322,657	18,171	57,387	202
2	2	10	50,0	50,0	258,268	9,429	35,392	201
3	6	6	27,5	50,0	336,859	9,157	53,343	287
4	6	6	5,0	27,5	613,091	50,07	82,244	287
5	10	2	50,0	5,0	529,43	16,615	74,019	283
6	2	6	27,5	27,5	259,695	9,013	43,605	248
7	2	10	50,0	5,0	486,754	96,945	59,17	201
8	10	2	5,0	5,0	782,038	67,808	92,087	283
9	6	6	50,0	27,5	338,943	8,81	51,441	287
10	2	2	5,0	5,0	592,156	22,021	88,926	287
11	2	2	50,0	5,0	324,6	17,045	50,919	201
12	2	10	5,0	50,0	522,783	16,774	77,727	287
13	2	10	5,0	5,0	757,489	79,536	83,837	287
14	10	2	50,0	50,0	264,243	10,485	38,409	199
15	6	6	27,5	27,5	458,097	11,303	62,862	287
16	6	6	27,5	5,0	592,849	50,795	79,841	286
17	10	6	27,5	27,5	525,424	16,238	78,225	283
18	10	2	5,0	50,0	519,07	83,877	59,913	199
19	2	2	50,0	50,0	54,173	7,587	15,014	116
20	6	2	27,5	27,5	259,297	9,723	46,546	248
21	10	10	5,0	5,0	979,725	113,258	94,346	281
22	10	10	5,0	50,0	712,985	62,825	79,991	283
23	10	10	50,0	5,0	705,519	68,107	78,302	281
24	10	10	50,0	50,0	460,192	10,928	58,752	283
25	6	10	27,5	27,5	522,832	15,295	75,62	287

Figure 3. Face-Centered Design (FCD) design layout defined in actual factors values. The responses in the red box are obtained from experiments on the simulation model.

3.4. DoE—Proposed Experimental Designs

To construct the metamodel of the production objectives, we were interested in two different experimental designs—the Box–Behnken Design (BBD) and Face-Centered Design (FCD). They were selected to explore and compare the suitability of both main types of spherical vs. cuboidal designs for the derivation of a metamodel of a simulation model. After screening experiments, we considered four factors on three levels (−1, 0, 1) in both types of experimental design and four responses F_1 – F_4 , representing the selected production goals (Table 1). The factorial space was a four-dimensional domain, with lower and upper bounds between values 2 and 10 pcs for the lot size and between 5 and 50 min for the product arrival time of both products. As responses, four selected production performance indicators were considered: the total number of products, average flow time, average machine utilization, and average costs per part unit. Both designs required 25 simulation runs each. The values of responses in each of the experimental points were found by simulation in Witness Horizon by Lanner Group Limited, Houston, TX, USA (see Figures 2 and 3, respectively). The BBD design layout for the actual values of the settings factors with the added responses that resulted from the simulation are shown in Figure 2. Similarly, Figure 3 depicts the experimental scheme with an added four responses for FCD.

Table 1. Factors and responses for design layouts.

Factor	Response
A—LotSizeP1	F_1 —Average flow time
B—LotSizeP2	F_2 —Average costs per part unit
C—IATP1	F_3 —Average machine utilization
D—IATP2	F_4 —Total number of products

3.5. The Particular MOOP Definition and Applied Scalar MOO Methods

The particular MOOP represents a task to design a set of four input parameters: the lot size and the input intervals for arriving supplies P1 and P2 within the specified ranges and production limitations while optimizing the production performance. Optimization involves minimizing the average costs per part unit and the average flow time and maximizing the total number of products and average machine utilization simultaneously.

To solve that, we applied two methods belonging to the class of scalarization methods with a priori defined preferences, referring to Marler and Arora [7].

Firstly, we constructed the scalar multi-objective U function in Equation (3) expressed through the Weighted Sum Method (WSM) as the linear combination of the normalized individual objectives $F_i^{transform}$ using the weight vector w . All components w_i have the same value 0.25 to not prefer any production goal.

$$U = \sum_{i=1}^k w_i F_i^{transform}, w_i > 0 \forall i, \sum_{i=1}^k w_i = 1 \quad (3)$$

Secondly, we applied the Weighted Product Method (WPM) with the same settings of weights defined by Equation (4). In both cases, minimizing the scalar U function leads to the single Pareto optimal solution finding.

$$U = \prod_{i=1}^k (F_i^{transform})^{w_i}, w_i > 0 \forall i, \sum_{i=1}^k w_i = 1 \quad (4)$$

There exist many possible transformations described e.g., by Marler and Arora [37] to ensure dimensionless objectives F_i entering the scalar multi-objective function. We employed a robust transformation given by Equation (5).

$$F_i^{transform} = \frac{F_i - F_i^U}{F_i^N - F_i^U} \quad (5)$$

That relates to a component of a utopia point vector and a nadir point vector, which represent the unreachable solutions for individual production goals as the best one (utopia) and as the worst one (nadir). The utopia point vector F^U can be taken as the optimum of the single-criterion function according to the optimization goal regardless of other objectives. F^N is the vector created by the worst values of the production goals. It can be determined by expert preferences or obtained from single-optimization experiments, too. Table 2 shows the applied values of these reference points. Value F_i in Equation (5) is a component of the production goals (individual objectives) vector that resulted from experiments on a discrete-event driven simulation model.

Table 2. Utopia and nadir point values in the transformation of objectives F_i .

Production Objective	Utopia Point F_i^U	Nadir Point F_i^N
Avg. flow time (min.)	296.309	550
Avg. costs per part unit (€)	10.209	16
Avg. machine utilization (%)	84.035	60
Total number of products (pcs)	289	230

For a numerical computation of the MOOP solution, we use the Evolutionary algorithm in MS Excel module Solver (by Microsoft, Redmond, WA, USA) to perform discrete global optimization.

The objective function employing WSM defined by Equation (3) and transformation in Equation (5) with the utopia and nadir points given by Table 2 was expressed via regression models of production goals based on FCD in the following analytical form, and it was minimized:

$$\begin{aligned}
 U = & 0.25 * (11.47091 + 6.53901 * LotSizeP1 + 7.91294 * LotSizeP2 - 1.42610 * IATP1 \\
 & - 1.40960 * IATP2 - 0.150095 * LotSizeP1 * IATP1 - 0.176751 * LotSizeP2 * IATP2 + \\
 & 0.030254 * IATP1^2 + 0.031313 * IATP2^2 - 10.209)/(16 - 10.209) + 0.25 * (91.78175 + \\
 & 0.626283 * LotSizeP1 + 0.301304 * LotSizeP2 - 0.923591 * IATP1 - 0.854483 * IATP2 + \\
 & 0.048977 * LotSizeP1 * IATP1 + 0.049608 * LotSizeP2 * IATP2 - 84.035)/(60 - 84.035) + \\
 & 0.25 * (250.66819 + 15.89178 * LotSizeP1 + 14.81886 * LotSizeP2 - 2.28272 * IATP1 - \\
 & 2.24722 * IATP2 + 0.238889 * LotSizeP1 * IATP1 + 0.237500 * LotSizeP2 * IATP2 - \\
 & 1.47246 * LotSizeP1^2 - 1.34746 * LotSizeP2^2 - 289)/(230 - 289) + 0.25 * (585.01423 + \\
 & 26.38960 * LotSizeP1 + 24.42893 * LotSizeP2 - 2.45189 * IATP1 - 11.04025 * IATP2 + \\
 & 0.119557 * IATP1^2 + 0.097507 * IATP2^2 - 296.309)/(550 - 296.309).
 \end{aligned} \quad (6)$$

Analogically, the minimized objective function designed on the base WPM with regression models that resulted from the FCD was expressed in the following form:

$$\begin{aligned}
 U = & (\text{ABS}(((11.47091 + 6.53901 * \text{LotSizeP1} + 7.91294 * \text{LotSizeP2} - 1.42610 * \text{IATP1} - \\
 & 1.40960 * \text{IATP2} - 0.150095 * \text{LotSizeP1} * \text{IATP1} - 0.176751 * \text{LotSizeP2} * \text{IATP2} + \\
 & 0.030254 * \text{IATP1}^2 + 0.031313 * \text{IATP2}^2 - 10.209)/(16 - 10.209)) * ((91.78175 + 0.626283 \\
 & * \text{LotSizeP1} + 0.301304 * \text{LotSizeP2} - 0.923591 * \text{IATP1} - 0.854483 * \text{IATP2} + 0.048977 \\
 & * \text{LotSizeP1} * \text{IATP1} + 0.049608 * \text{LotSizeP2} * \text{IATP2} - 84.035)/(60 - 84.035)) * \\
 & ((250.66819 + 15.89178 * \text{LotSizeP1} + 14.81886 * \text{LotSizeP2} - 2.28272 * \text{IATP1} - 2.24722 \\
 & * \text{IATP2} + 0.238889 * \text{LotSizeP1} * \text{IATP1} + 0.237500 * \text{LotSizeP2} * \text{IATP2} - 1.47246 \\
 & * \text{LotSizeP1}^2 - 1.34746 * \text{LotSizeP2}^2 - 289)/(230 - 289)) * ((585.01423 + 26.38960 \\
 & * \text{LotSizeP1} + 24.42893 * \text{LotSizeP2} - 12.45189 * \text{IATP1} - 11.04025 * \text{IATP2} + 0.119557 * \\
 & \text{IATP1}^2 + 0.097507 * \text{IATP2}^2 - 296.309)/(550 - 296.309))) ^ 0.25.
 \end{aligned} \quad (7)$$

Both optimization models based on WSM and WPM multi-objective methods defined by Equations (6) and (7) included the constraints for the production goals listed in Table 3. The objective functions domain was constrained by preliminary simulation experiments. The design space was constrained by lower and upper bounds in a range from 2 to 10 pcs for both supplies' lot size, and 5 to 50 min for the time between the supplies' arrivals.

Table 3. Constraints for the vector of production objectives.

Production Objective	Constraint
Average flow time (min.)	$F_1 \leq 550$
Average costs per part unit (€)	$F_2 \leq 16$
Average machine utilization (%)	$F_3 \geq 60$
Total number of products (pcs)	$F_4 \geq 230$

3.6. Numerical Optimization via Maximizing Desirability Function

The second numerical approach is multi-response optimization based on the Desirability function maximization in software Design-Expert® version 12 (by Stat-Ease, Minneapolis, MN, USA) where surrogate models for individual objective functions were built. Montgomery [35] describes a multiple response method that employs an objective function D , which is called the Desirability function. It reflects the desirable ranges for each individual response d_i simultaneously. Equation (8) defines the value d_i if the target T for the response y is a maximum value, and Equation (9) defines the value d_i if the target T is a minimum value, respectively.

$$d_i = \begin{cases} 0 & y < L \\ \left(\frac{y-L}{T-L}\right)^r & L \leq y \leq T \\ 1 & y > T \end{cases} \quad (8)$$

$$d_i = \begin{cases} 1 & y < T \\ \left(\frac{U-y}{U-T}\right)^r & T \leq y \leq U \\ 0 & y > U \end{cases} \quad (9)$$

Exponent r determines how strictly the target value is desired. For $r = 1$, the desirability function increases linearly toward T ; otherwise, the value r causes a convex or concave function property. For k transformed responses, the simultaneous objective function D is a geometric mean (10) of all d_i :

$$D = \left(\prod_{i=1}^k d_i \right)^{1/k}. \quad (10)$$

Numerical optimization via the D function demands a range of factors, responses, and optimization goals in the settings. The applied settings of these parameters are listed in Table 4. The limits of functions in the form of ramps for individual responses d_i are depicted in Figure 4. It shows the graphs of d_i functions in Equations (8) and (9) for specified limit values on individual intervals. Two of the notches on each ramp represent the minimum and maximum values of all response values within the experimental space, and two others are lower and upper limits for the given response. They correspond to L and U values in Equations (8) and (9), respectively (the lower and upper limit in Table 4). At the same time, they correspond to the utopia and nadir points as reference points in other types of applied scalar multi-objective functions.

Table 4. Optimization goals and ranges for factors in the maximization D function approach.

Optimization Goal	Lower Limit	Upper Limit
A is in range	2	10
B is in range	2	10
C is in range	5	50
D is in range	5	50
F_1 —minimize	296.309	550
F_2 —minimize	10.209	16
F_3 —maximize	60	84.035
F_4 —maximize	230	289

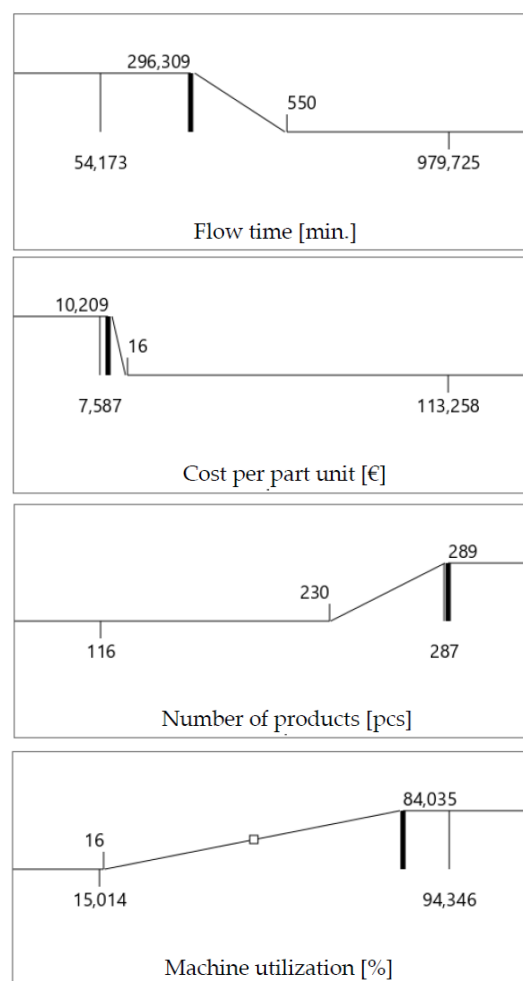


Figure 4. Ramp graphs with $r = 1$ show minimum, maximum, and lower and upper limits for individual responses d_i .

3.7. Validation of Proposed MOOP Solving Strategy

To validate the solutions calculated via proposed optimization models, we consequently performed simulation-based optimization of both *U* functions applying metaheuristic (Adaptive Thermostatic Simulated Annealing). In addition, the brute force algorithm All Combinations in the Witness module Experimenter (Lanner Group Limited, Houston, TX, USA) was performed in Advanced Mode under the same conditions, as previous numerical experiments were conducted. The design space was the same four-dimensional domain, with lower and upper bounds between values 2 and 10 pcs for the lot size and between 5 and 50 min for the supply arrival time for both products. The objective functions domain was constrained by the values listed in Table 3. For all optimization experiments, the length of simulation was 1440 min with a 100 min warm-up period.

The WSM-derived scalar objective function employed Equation (3) and the transformation expressed by Equation (5). Utopia and nadir points are given in Table 2. It was defined in an optimization model in the form shown in Box 1.

Box 1. Definition of Weighted Sum Method (WSM)-based objective function in a simulator.

```
IF Number_of_products >= 230 AND Costs_per_part_unit <= 16 AND Flow_Time <= 550 AND
Machine_Utilization >= 60
RETURN 0.25 * (Costs_per_part_unit - 10.209)/(16 - 10.209) + 0.25 * (Machine_Utilization -
84.035)/(60 - 84.035) + 0.25 * (Number_of_products - 289)/(230 - 289) + 0.25 * (Flow_Time - 296.309)/(550 -
296.309)
ELSE
RETURN 0.25 * (Costs_per_part_unit - 10.209)/(16 - 10.209) + 0.25 * (Machine_Utilization - 84.035)/(60 -
84.035) + 0.25 * (Number_of_products - 289)/(230 - 289) + 0.25 * (Flow_Time - 296.309)/(550 - 296.309) + 100
ENDIF
```

In the case of the WPM method, we used the definition of objective function body formulated in Box 2.

Box 2. Definition of WPM-based objective function in the simulator.

```
IF Number_of_products >= 230 AND Costs_per_part_unit <= 16 AND Flow_Time <= 550 AND
Machine_Utilization >= 60
RETURN ((Number_of_products - 289)/(230 - 289)) ** 0.25 * ((Costs_per_part_unit - 10.209)/(16 - 10.209)) **
0.25 * ((Flow_Time - 296.309)/(550 - 296.309)) ** 0.25 * ((Machine_Utilization - 84.035)/(60 - 84.035)) ** 0.25
ELSE
RETURN ((Number_of_products - 289)/(230 - 289)) ** 0.25 * ((Costs_per_part_unit - 10.209)/(16 - 10.209))
** 0.25 * ((Flow_Time - 296.309)/(550 - 296.309)) ** 0.25 * ((Machine_Utilization - 84.035)/(60 - 84.035)) ** 0.25
+ 100
ENDIF
```

Due to minimization, when the conditions for the production goals' constraints were not fulfilled, the value of the objective function was increased by 100.

4. Results

4.1. Derivation of Surrogate Models of Production Objectives

To fit the response surface, we performed DoE with two types of response surface designs, Face-Centered Design (FCD) and Box–Behnken Design (BBD) for four factors in Design-Expert® software by Stat-Ease (Minneapolis, MN, USA). It provided the polynomial regression models for four selected production objectives as models of the input–output behavior of the underlying simulation model. Based on the ANOVA analysis by F-test of the overall statistical significance of the model and t-tests of the statistical significance of individual regression coefficients, Equations (11)–(18) in terms of actual factors represent obtained response surface models for both types of design. The Lack of Fit test

could not be performed due to no variance in the central point, because the applied simulation model has been deterministic.

As for BBD, the fitting model was linear for the average flow time and machine utilization responses according to Equations (11) and (13); others were reduced quadratic models for costs per part unit and number of products regarding to Equations (12) and (14).

$$\text{Flow time} = 435.07580 + 125.17042 * \text{LotSizeP1} + 120.09642 * \text{LotSizeP2} - 138.29592 * \text{IATP1} - 133.84925 * \text{IATP2} \quad (11)$$

$$\begin{aligned} \text{Costs per part unit} = & 12.51314 + 5.7129 * \text{LotSizeP1} + 5.60725 * \text{LotSizeP2} - \\ & 18.85525 * \text{IATP1} - 19.27592 * \text{IATP2} - 11.10425 * \text{LotSizeP1} * \text{IATP1} - 12.24525 * \\ & \text{LotSizeP2} * \text{IATP2} + 16.61164 * \text{IATP1}^2 + 17.40139 * \text{IATP2}^2 \end{aligned} \quad (12)$$

$$\text{Machine utilization} = 64.56492 + 12.97700 * \text{LotSizeP1} + 11.51400 * \text{LotSizeP2} - 14.87858 * \text{IATP1} - 13.25308 * \text{IATP2} \quad (13)$$

$$\begin{aligned} \text{Number of products} = & 274.30769 + 18.33333 * \text{LotSizeP1} + 19.41667 * \text{LotSizeP2} - \\ & 7.16667 * \text{IATP1} - 6.75000 * \text{IATP2} + 21.50000 * \text{LotSizeP1} * \text{IATP1} + 21.75000 * \\ & \text{LotSizeP2} * \text{IATP2} - 15.80769 * \text{LotSizeP1}^2 \end{aligned} \quad (14)$$

The final equations in terms of the actual Equations (15)–(18) represent models with statistically significant coefficients based on FCD. Almost all the FCD-based models are reduced quadratic models, besides the model for machine utilization, which is linear with interactions.

$$\text{Flow time} = 585.01423 + 26.38960 * \text{LotSizeP1} + 24.42893 * \text{LotSizeP2} - 12.45189 * \text{IATP1} - 11.04025 * \text{IATP2} + 0.119557 * \text{IATP1}^2 + 0.097507 * \text{IATP2}^2 \quad (15)$$

$$\begin{aligned} \text{Costs per part unit} = & 11.47091 + 6.53901 * \text{LotSizeP1} + 7.91294 * \text{LotSizeP2} - \\ & 1.42610 * \text{IATP1} - 1.40960 * \text{IATP2} - 0.150095 * \text{LotSizeP1} * \text{IATP1} - 0.176751 * \\ & \text{LotSizeP2} * \text{IATP2} + 0.030254 * \text{IATP1}^2 + 0.031313 * \text{IATP2}^2 \end{aligned} \quad (16)$$

$$\begin{aligned} \text{Machine utilization} = & 91.78175 + 0.626283 * \text{LotSizeP1} + 0.301304 * \text{LotSizeP2} - \\ & 0.923591 * \text{IATP1} - 0.854483 * \text{IATP2} + 0.048977 * \text{LotSizeP1} * \text{IATP1} + 0.049608 * \\ & \text{LotSizeP2} * \text{IATP2} \end{aligned} \quad (17)$$

$$\begin{aligned} \text{Number of products} = & 250.66819 + 15.89178 * \text{LotSizeP1} + 14.81886 * \text{LotSizeP2} - \\ & 2.28272 * \text{IATP1} - 2.24722 * \text{IATP2} + 0.238889 * \text{LotSizeP1} * \text{IATP1} + 0.237500 * \\ & \text{LotSizeP2} * \text{IATP2} - 1.47246 * \text{LotSizeP1}^2 - 1.34746 * \text{LotSizeP2}^2 \end{aligned} \quad (18)$$

The selected characteristics of analytical models for four production objectives, created via BBD and FCD designs, are shown in Tables 5 and 6. With respect to the results of modeling, we apply only the better, FCD-based metamodel of a black-box function in the further surrogate-based optimization.

Table 5. Characteristic of regression models resulted from BBD.

Response	R ²	Adj. R ²	Pred. R ²	Std. Dev.
Flow time	0.887	0.864	0.821	71.67
Costs per part unit	0.931	0.896	0.766	7.82
Number of products	0.768	0.672	0.368	16.35
Machine utilization	0.901	0.881	0.842	6.80

Table 6. Characteristic of regression models resulted from Face-Centered Design (FCD).

Response	R ²	Adj. R ²	Pred. R ²	Std. Dev.
Flow time	0.991	0.988	0.985	22.75
Costs per part unit	0.945	0.918	0.858	9.37
Number of products	0.968	0.952	0.942	10.19
Machine utilization	0.943	0.924	0.906	5.48

4.2. Results of Numerical Optimizations

The numerical optimization of scalar MOO functions involved two different approaches. We performed the global discrete minimization using the Evolutionary algorithm in the module Solver in MS Excel (by Microsoft, Redmond, WA, USA) for selected scalar MOO methods under the constraints specified in Table 4. We implemented the FCD models defined by Equations (15)–(18) into *U* functions only due to the better prediction ability of these models. Next, we found the solution via the Desirability function maximization for FCD models in the numerical optimization module of Design-Expert® by Stat-Ease (Minneapolis, MN, USA). The results are presented in Tables 7–9.

Table 7. Experiment results using the WSM multi-objective optimization method.

Applied Model	Algorithm	Factors/Input Parameters in Design Space				Responses/Production Objectives in Objective Space			
		A	B	C	D	Flow Time	Costs Per Part Unit	Number of Products	Machine Utilization
FCD model	Evolutionary alg. Module Solver (Excel ¹) <i>U</i> = 0.333	6	7	29	34	391.15	10.21	286.21	62.14
Simulation model	Simulation- optimization All Combinations Module Experimenter (Witness ²) <i>U</i> = 0.269	3	3	10	30	305.13	10.58	288	60.99
Verification	Simulation (Witness ²)	6	7	29	34	446.98	10.77	288	60.31

¹ by Microsoft, Redmond, WA, USA; ² by Lanner Group Limited, Houston, TX, USA.

Table 8. Experiment results using the WPM multi-objective optimization method.

Applied Model	Algorithm	Factors/Input Parameters in Design Space				Responses/Production Objectives in Objective Space			
		A	B	C	D	Flow Time	Costs Per Part Unit	Number of Products	Machine Utilization
FCD model	Evolutionary alg. Solver module (Excel ¹) <i>U</i> = 0.0271	8	7	42	31	406.5	10.22	287.50	60.84
Simulation model	Simulation-Optimization All Combinations Module Experimenter (Witness ²) <i>U</i> = 0.051	2	5	7	46	335.59	10.216	287	60.093
Verification	Simulation (Witness ²)	8	7	42	31	459.16	10.93	286	60.22

¹ by Microsoft, Redmond, WA, USA; ² by Lanner Group Limited, Houston, TX, USA.

Table 9. Experiment results using the Desirability function multi-objective optimization method.

Applied Model	Algorithm	Factors/Input Parameters in Design Space				Responses/Production Objectives in Criterion Space			
		A	B	C	D	Flow Time	Costs Per Part Unit	Number of Products	Machine Utilization
FCD model	Numerical optimization Multi-response method (Design-Expert® ¹) $D = 0.631$	6	2	26	11	433.20	10.21	274.49	70.98
Verification	Simulation (Witness)	6	2	26	11	428.55	10.87	287	60.84

¹ by Stat-Ease, Minneapolis, MN, USA.

4.3. Validation of Approximate MOOP Solving Strategies

The comparison of results achieved by different numeric and simulation-based optimization methods for WSM and WPM is presented in Tables 7–9. In addition, the table also includes the verification of results obtained via surrogate-based optimization by simulation.

5. Discussion

Having been inspired by [17], we applied the DoE technique for the derivation of a surrogate model of a simulation model for a batch production system, namely Face-Centered Design (FCD) and Box–Behnken Design (BBD). Referring to Montgomery [35], the designs chosen were two very frequently used ones with different properties regarding prediction ability.

With respect to the selected type of the response design, the results indicate that the FCD generated a very good regression model with better prediction precision for all four responses comparing to BBD. Therefore, only the analytical model derived on the base of FCD was applied in the objective functions when performing numerical multi-objective optimization.

As for FCD applied in optimization, in spite of its good characteristics, the analysis of results presented in Tables 7–9 does not show a full consonance in the solutions found through different methods. The solutions, which resulted from simulation-based optimization via a brute force algorithm, have a very short Flow time component and they differ from surrogate-based solutions in this component significantly for both WSM and WPM methods. It implies that the Flow time function is very sensitive to the change of system loading, and the approximation of real values of this component by the FCD response surface model leads to results that are unacceptable for settings in a control process.

Despite this, if we look at the results in more detail, the match confirmed by the simulation is visible for three other components of the MOO solution vector in an objective space. The deviations for these three production objectives (the average costs per part unit, the total number of products, and the average machine utilization) are in an acceptable range (maximally 3.1%) other than the values that resulted directly from the maximization of Desirability function. The solutions that resulted from using this method are strongly influenced by the setting of method parameters. All substantial differences can be partially explained by an approximation error effect, parameters methods settings, and by the lack of guarantee to find a global solution using the heuristic method in case of an Evolutionary algorithm.

We also compare all numerically obtained MOOP solutions related to using metamodels to the values originated from simulation. All these solutions have offered such design variables that the corresponding production goals resulted from the simulation output are mostly dominated by solutions obtained by the All Combinations algorithm using simulation-based optimization. We can conclude that for a real practice, fast obtained solutions that originate from numerical optimization based on FCD are not so good in the sense of Pareto optimality. On the other hand, they can represent approximate values that are rather close enough to effective solutions in a design space for control purposes considering only production goals, which are not too sensitive to the change of input parameters. Regardless of the different locations of the points in design space, all applied surrogate-based multi-objective

optimization methods provide similar solutions in terms of the components of the production objectives vector within the specific transformation and weight vector. When comparing this, all solutions verified by simulation are very close to each other in objective space.

The literature concerning metamodel-based solving MOOP [11,16] indicates that the utilization of valid metamodels can shorten the computational time needed for optimization processes, namely in the optimization of expensive black-box functions. We observed a significant shortness of calculation time when applying both numerical approaches in contrast to simulation-based optimization, but the time for searching for MOOP solutions strongly depended on the parameters of the applied methods. According to the authors' best knowledge, there is no similar work that can be used for comparison conclusions due to the specifics of the underlying discrete-event driven simulation model.

To discuss the limitations of the presented MOOP solving procedure based on surrogates, the three main following limitations should be mentioned:

1. We assume that an adaptable simulation model of the production system must be built.
2. We assume that the controlled production system does not involve too fast inner parameters and structural changes. The inner parameters and structure can be flexible, but they need to be changed in hours, not in minutes. Even if the simulation model could reflect changes almost immediately, the steps of the designed MOOP procedure take some time to derive the surrogate model and consequently find the solutions.
3. We must consider that some of the production goals are too sensitive to the change of input parameters; therefore, the approximate solution is not satisfactory.

6. Conclusions and Future Work

In this paper, we presented the procedure for approximate MOOP solving via the surrogate model of a simulation model for the studied batch production system. The MOOP was focused on the simultaneous optimization of four selected production goals. We derived the surrogate model by applying an integration of simulation and DoE technique using Face-Centered Design (FCD) and Box–Behnken Design (BBD). The prediction ability of the model derived from the FCD was observed better than that from the BBD. Thus, only the model that originated from FCD was consequently applied for generating objective functions in the numerical solving of the MOOP.

We can conclude that for a real practice, the solutions that originated from the numerical optimization based on FCD can represent approximate values that are rather close enough to effective solutions in the design space for control purposes when we consider only production goals, which are not too sensitive to the change of input parameters. The advantage is that they are available much faster (in minutes) than solutions that resulted from the long-lasting simulation-based optimization process (in hours or days).

On the basis of the study results, we suppose that the obtained result of optimization is acceptable for control purposes for the studied production system. Of course, this conclusion cannot be generalized based on solutions corresponding to one specific simulation model. The potential wider applicability of the designed procedure in manufacturing control is limited by the results of another research study. When comparing the findings gathered within this study on other production systems, clearer conclusions can be pronounced for all systems that fulfill the assumptions outlined above.

From this point of view, the future interest can be focused on testing other types of surrogate models that could be able to increase the precision of numerical solving MOOP regarding the sense of closeness to Pareto optimal solutions. Additionally, the possibility of applying other multi-objective methods to find solutions in a nonconvex part of a Pareto front also can be investigated. After that, analogic experiments using stochastic models of production systems could be performed.

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