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Design and analysis of simulation experiments

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Abstract: In the competitive environment of global markets, it is necessary to constantly improve production processes in order to achieve high quality products while maintaining low costs. This article discusses the importance of properly designed simulation experiments and experimental planning in optimizing manufacturing systems. Simulation experiments allow to investigate system dependencies and then use the results to reduce costs, reduce development time and bring new products to market. Experimental planning plays an important role in this to help identify the most influential inputs, eliminate unwanted distractions, and gradually increase production performance. The article discusses the issue of different types of simulation experiments, from active and passive to model experiments, and also emphasizes the key function of factor interactions in the design of 2^k and 3^k plans. The result is an overview of the planning and management of simulation experiments, which indicates how to effectively use simulation models in industrial production conditions.

1 Introduction

Simulation experiments are among the important tools for investigating and analyzing complex systems and processes, especially in cases where analytical solutions or physical experiments are not feasible. Computer simulation is often characterized as a research method in which a real dynamical system is replaced by its model (simulator) and experiments are carried out on it in order to gain knowledge about the original system [1]. Such an approach makes it possible to safely test various hypotheses and scenarios without interfering with the real environment and without the risk of disrupting operations [2]. The simulation is used in a wide range of areas from engineering disciplines (production, logistics, transport) to economics and social sciences, providing a basis for qualified decision-making based on virtual experiments. In industrial production, the use of simulation is of paramount importance – it allows you to analyze and optimize production processes without the need to interrupt real operation, which leads to cost reduction and improvement of production quality. At the same time, simulation technologies reduce the time needed to develop and bring new products to market by detecting potential problems at the design stage and reducing the need for expensive prototyping [3]. These benefits make simulation an integral part of modern engineering and strategic production management. The aim of this review article is to provide a comprehensive view of the use of simulation experiments in the optimization of production processes and to summarize current knowledge in this field. Its contribution lies in the synthesis of the current state of knowledge and the identification of trends and challenges, thus contributing to a better understanding of the role of simulations in the modern production environment.

2 Methodology

Competitors everywhere in the world strive to produce high-quality products at a reasonable price. This is possible if the manufacturer manages its production processes efficiently. Success in the market for quality products today requires short product development and market times, low production costs, high quality (low variability and low number of defective products) and short lead times. When applying simulation, we use simulation experiments for the analysis of system dependencies. However, the experiments themselves must be preceded by their preparation (planning), otherwise we are looking for a needle in a haystack. Simulation experimentation usually involves a large number of simulation runs (experiments) to ensure sufficient statistical independence and accuracy of simulation results. Planning and management of simulation experiments deals with the tasks of planning the number and determining the order of simulation runs, determining the necessary length of the simulation, its start-up period, etc. [4]. Planning experiments supports performance growth, reduction of production costs and optimization of production plan. A good experiment plan makes it possible to study the causes of process variability, reduce them based on the result of experiments and thus increase production performance. Customers expect quality products and if they do not receive them, it costs the manufacturer additional costs (for example complaints, returns of goods that are under warranty). The outputs from the implementation of a good experimental plan allow to reduce costs (for example fewer defective products, reduction of the number of repairs of defective parts, release of capacities). When developing products and planning production processes, managers usually try to vary the values of one factor and monitor the effect of such changes on the output. Conventional planning procedures do not allow for the simultaneous variation of a large number of factors that can simultaneously take on a large number of levels, nor do they allow for mutual combinations (interactions) of different factors and their levels. Good experimental plans allow for a significant reduction in time to market and short lead times for production [5]. Let's look at a diagram of a typical production process (see Figure 1). Each production process has a set of inputs (input sources and input factors) that affect the course of the production process and thus its outputs (responses). A manufacturing process can have a whole set of outputs. Every manager wants to know how certain input values affect the outputs of the production process.

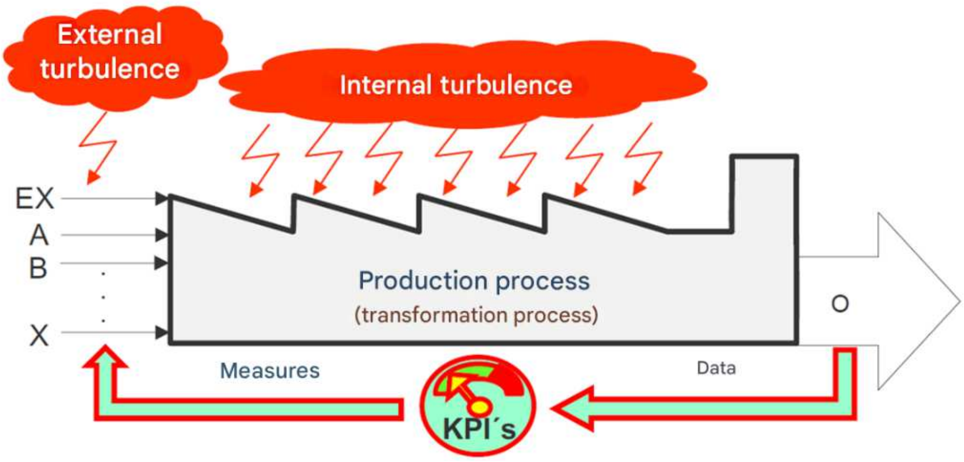

Figure 1 Typical production process

A tool for understanding the causal relationship between the change of inputs of the production process and its outputs is the planning of experiments (Design of Experiments - DoE). A statistical method for evaluating the dependence between inputs and outputs of the investigated system is regression analysis. However, the use of this method is problematic, with a large number of factors it is difficult to determine the influence of individual factors on the output, in case the factors are strongly correlated (the problem of multicollinearity). Due to the strong correlation dependence of input factors, the term confounding is used in the planning of experiments. Planning experiments makes it possible to determine which inputs have the most significant effect on the outputs of the production process and its variability, which allows the system to be optimized. Another task in the planning of experiments is to determine the values of inputs (factor levels) so that the "optimal" output is achieved. If we know the significant factors and their levels, then we can create a descriptive linear regression mathematical model for each output response and its input factors (and combinations of several factors - interactions), which will be a representation of the effects of the given factors on the output of the production process. If the relationship between inputs and outputs is not linear, then the importance of experiment planning decreases. It is most advantageous to apply the planning of experiments in the design (design) and planning of production processes, when it is also most effective to apply simulation. Despite this knowledge, experimental planning and simulation are most often applied when the production process is already running in routine operation. The input variables to the production process can be divided into controlled variables (which we will change in the experiment in a planned manner) and uncontrolled. The requirement in experimentation is that the controlled input variables are independent, that is, uncorrelated. The experimenter's effort is to randomize the uncontrolled inputs, which means to average the effects of the uncontrolled inputs. For example, the following dealt in detail with the issue of planning experiments in simulation [6-8].

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2.1 Types of simulation experiments

Depending on the goals that we pursue through experimentation, we distinguish different types of experiments (see Figure 2):

Active and passive experiment

Active experiment - an active change in the initial conditions of the experiment (the levels of factors and the factors themselves change) with respect to the effects already obtained during the experimentation.

Passive experiment - registering the values of an output parameter under a certain system of conditions. Individual factors and their values do not change during the experiment.

Descriptive and optimization experiment

Descriptive experiment - identifies the area of reactions. Interpolation and extrapolation methods are used for data processing. Such an experiment is used for research, analysis, or comparison.

Optimization experiment - determines the optimal levels of factors. Thus, these are synthesis tasks.

Normal and accelerated experiments

Normal experiment - requires the provision of conditions close to real ones

Conditions

Accelerated experiment - the goal is to speed up the experimentation procedure.

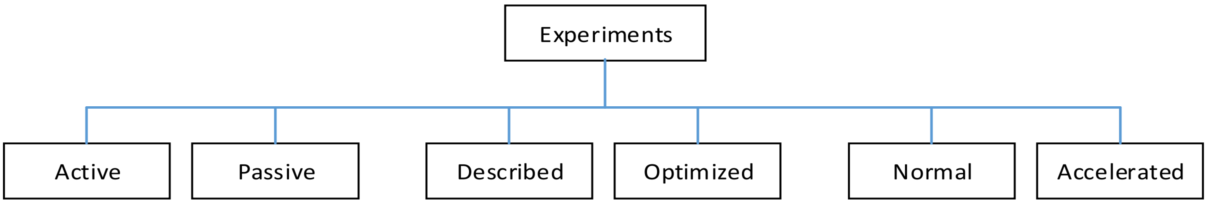

Figure 2 Types of simulation experiments

From the point of view of simulation experimentation, we will distinguish three types of experiments:

Screening – a small number of pilot trials, the aim of which is to sort out (reduce) the number of factors and select only the most influential ones.

Classical (physical) experiments – this is a classic experimentation with a real production system, i.e. responses are obtained by direct measurement or observation of the production system. Directly in production, we can measure, for example, production output, stocks of work-in-progress, continuous production times, or equipment failure rate. In the case of this type of experiments, we need to analyze the noise in the data, which consists of two components: experiment noise and measurement noise.

Model experiments – this is experimentation with a model (for example mass service system, queue networks, simulation model, simulation metamodel, analytical model) of a production system that we will use as a substitute for a real production system. The responses will be directly output statistics from the given model. Also in this case, we need to analyze the noise in the data, which takes the form of model noise (for example the influence of random number generators, the effect of adaptation distributions) and experimentation noise (for example start-up time, simulation length).

2.2 The principle of planning experiments

Relationship between input factors and output responses of the system to changes in levels factors is shown in Figure 3.

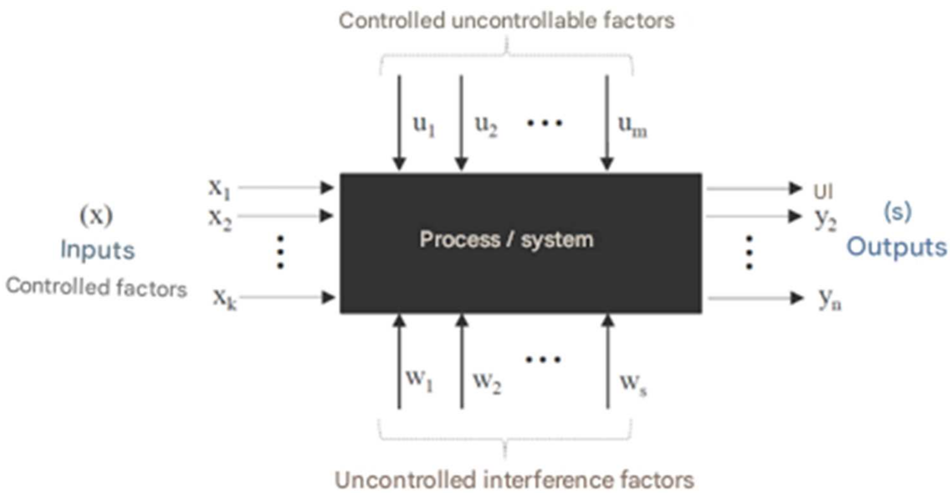

Figure 3 Relationship between input factors and responses

As can be seen from Figure 3, in process modeling we have a set of input factors x1, x2, ..., xk, entering the process, the outputs of which are the responses y1, y2, ..., yn. In this case, the process is represented as a black box, so we cannot express the transformation process that transforms inputs into outputs explicitly. The best solution would be to describe the physical relationships between inputs and outputs, but this is often impossible or too complicated in practice. Therefore, the practice uses a simpler solution, representing the given transformation model using a substitute mathematical model, valid for the area of defined input factor levels.

The inputs in Figure 3 contain a subset of input quantities, which we also call factors, and their more detailed description is given in the next section. In the experiment, we will vary the levels of factors, while keeping the values of the other input quantities at a constant level. Factors can be divided into controlled (by changing them, we affect the responses of the process), controlled but uncontrolled (they are constant during the experiment, they are not subject to investigation) and uncontrolled and uncontrolled, or disturbing (for example they represent random influences, such as disturbances, turbulence), they are the cause of the dispersion of responses). In the course of the experiment, we will also be interested in the simultaneous action of a combination of several factors, which we call interactions. When experimenting, we use only the most influential factors. These are determined at the beginning of the experiment, in the process of so-called screening, most often using sensitivity analysis. As factors vary, we'll assign specific values to each factor, which we refer to as levels or factor levels. The set of all combinations of factor levels forms the experimental space. To reduce the exploding number of attempts, plans with two levels of factors, known as 2^k plans, are most often used. The analyzed process responds to the variation in the levels of input factors with specific outputs, which are also referred to as responses. In the case of simulation, the responses are directly output statistics. The set of responses of the experiment forms the response surface. The responses on the basis of which we will optimize the properties of the investigated process will also be called parameters. In the case of planning experiments, an experiment is called the search for process responses to a single setting of factor levels. The experiment represents a defined combination of levels for all the factors under investigation and is represented in the experiment plan by the experiment matrix row. It is the basic unit of the experiment. In a simulation, an experiment is represented by a simulation run. A structured set of experiments for a selected group of k-factors that can acquire q-levels, while we change the levels of individual factors in a planned manner within the experiments, is called an experiment. The significance of the influence of individual factors and their interactions is also called the effects of the given factors. We can determine the values of the effects only after the experiments have been carried out. The values of factor effects at a given factor level are determined as the average value of the difference between the responses at the upper level of the factor and the responses at the lower level of the factor. Factor effects allow us to rank all factors according to their significance. The process of ranking factors based on their significance is called ranking and we use the rank correlation method. Based on the ranking of factors, the experimenter can decide, for example, to reduce the number of factors in the experiment, or to use this knowledge to optimize the properties of the analyzed system. Experimental planning is an approach that allows to investigate the causality between changes in the levels of input factors and the values of the output parameters of the analyzed process, for which it uses Design of Experiments (DoE), i.e. a set of planned experiments. A plan of experiments is a set of experiments in which the levels of input factors are varied in a planned manner and the responses of the investigated system to these variations are monitored. Most often, the experiment plan is represented using an experiment matrix, in which the columns represent the individual factors (and their interactions) and the rows represent different combinations of the levels of the factors under investigation (experiments). If we verify the influence of all factors and their levels in experimentation, then we refer to such experiments as Full Factorial Experiments (FFE). If the number of factors or their levels is reduced, then we speak of Fractional Factorial Experiments (FRFEs).

We define the individual elements of the experiment plan as follows:

Number of factors - fj , j ε 〈1, k〉
Number of Factor Levels – lt, t ε 〈1, q〉
Number of attempts - ri , i ε 〈1, n〉

Given a known number of factors and their levels, we can determine the number of necessary trials n = q^k where n – number of attempts needed, q – number of factor levels, k – number of factors.

If we know the number of attempts (n), we can also determine the total number of factors and their interactions (FI) FI = n-1.

If the number of factors is known, then we can easily determine the number of all factor interactions (Is), according to the relation Is = n-1-k = q^k - 1 – k , s = k+1, ..., n-1-k.

When planning experiments, it is essential to distinguish between two fundamental concepts: the number of factor levels (q) and the order of an interaction.

1. The number of factor levels (q) defines how many different settings or values each factor will have during the experiment. The most common types are:

- q=2: Each factor has two levels, typically a lower (-1) and an upper (+1) setting. Experimental plans using this structure are called 2^k factorial designs. They are highly efficient for identifying significant factors and their effects.

- q=3: Each factor has three levels, often denoted as lower (-1), central (0), and upper (+1). These 3^k factorial designs are useful for detecting non-linear relationships (curvature) in the response.
- For q ≥ 4, the levels are usually denoted by numbers (1, 2, 3, 4, ...).

2. The order of an interaction refers to the number of factors that are jointly affecting the output response.

- Main effects are the effects of individual factors (e.g., A, B). They can be considered first-order effects.
- A second-order interaction represents the combined effect of two factors (e.g., A×B or B×C).
- A third-order interaction involves three factors (e.g., A×B×C).

It is crucial to understand that these two concepts are independent. For example, even in a simple 2^k design (where q=2), it is possible to study second-order (A×B), third-order (A×B×C), and even higher-order interactions, provided the experiment includes enough factors. The original text's direct link between q=2 and second-order interactions was incorrect.

At q = 3 - three levels are used, most often referred to as lower (-), basic (0) and upper (+). These plans are of the 3k type.

For q = 4 and more, we use the denotation of levels with the digits 1, 2, 3, 4, ...

For an approximate representation of the investigated processes, we look for an explicit form of a descriptive model in the course of experimentation, which is most often expressed in the form of a linear regression model. In special cases, quadratic models are also used. As many experiments have shown, the weight of interactions in linear models decreases significantly as their order increases. Second- and third-order interactions are the most used. Higher orders of interaction usually do not affect responses significantly and their effect is usually very small (we neglect it). Let us illustrate the importance of interactions with a simple example of an analysis of the production system.

3 Results

Our task is to investigate the influence of three factors on the lead time of the production batch. To solve the problem, we will use a simple approach of creating an experiment plan known as OVAT (One Variable At a Time). Actual and coded factor levels are shown in Table 1.

As can be seen from Table 2, when using the OVAT experiment plan, we change the levels of only one factor, while the levels of the other factors remain at a constant level (they do not change).

Table 1 Actual and coded factor levels

Factor	Factor meaning	Unit	Lower level (-1)	Upper level (+1)
A	Input intensity	pcs./min	3	22
B	Batch size	pcs.	10	100
C	Buffer capacity	pcs.	7	34

The plan of OVAT experiments for the situation described above is presented in Table 2.

Table 2 Experimental plan for OVAT

Run	Factor			Production lead time (min)
	A	B	C	
1	-1	-1	-1	7.56
2	+1	-1	-1	11.25
3	+1	+1	-1	12.76
4	+1	+1	+1	21.8

The first attempt represents a situation where all factors are set to the lower level (-1). In the second experiment, we change the level of factor A to the upper level and the remaining factors B and C remain set at the lower level, i.e. we keep them at a constant level (we do not change the values of their levels). We determine the levels for the third and fourth experiments by analogy. As can be seen from Table 2, the smallest lead time was achieved in Experiment 1, i.e. based on the OVAT approach, we would conclude that the best combination of factor levels is found in the first experiment. Let's analyze the effects of the factors further. The difference in the responses of the first column (factor A) of experiment 1 and experiment 2 will represent an estimate of the effect of factor A. We will determine the effect of the factor as the difference in the values of the responses at its upper level (+1) and its lower level (-1). In our case, for the effect of factor A, A = A+1 - A-1 will be valid, then we will determine the value of the effect as A = 11.25-

7.56 = 3.69 min. From Table 2 it is clear that the estimation of the effect of factor A was made when setting both factors B and C at the lower level (-1). Therefore, the OVAT approach does not guarantee that the effect of factor A will be the same even if we change the levels of factors B and C, exactly only if these factors are set to the lower level. Similarly, we can determine the effects of factors B and C.

From the combinations of factor levels listed in Table 2, it is clear that combinations (A-1, B+1), (A-1, C+1), (B-1, C+1) are missing. The fact that we do not investigate the effects of missing combinations of factor levels in the OVAT approach means that we have not obtained enough information from experimentation to implement reliable conclusions, which can lead to erroneous decisions about the optimal combination of factor levels studied. The above-mentioned missing combinations of factor levels are called interactions. These occur when the effect of one factor depends on the levels of other factors in the experiment, which also means that the effect of one factor level is different when we change the levels of another factor. To investigate the effects of interactions that arise between different factor levels, we need to change all factor levels at the same time. This can be done, for example, in a full factorial experiment (FFE), in which we investigate all possible combinations of factor levels and their interactions. For the case of the three factors, the FFE would require the implementation of 8 experiments (23), while the experimental plan would include the natural factors A,B,C, their second-order interactions AB, AC, BC and one third-order interaction ABC. FFE will already make it possible to investigate all the dependencies between factors A, B, C and their interactions. In this simple example, we would determine the effect of the interaction between the levels of two factors (for example, A,C) according to the following relationship (1):

$$I_{A,C} = \frac{E_{A,C^{+1}} - E_{A,C^{-1}}}{2} \qquad (1)$$

The symbol EA,C+1 indicates the effect of factor A if factor C is set at the upper level, and the symbol EA,C−1 indicates the situation when factor C is set to the lower level. As seen in the relation, we calculate the interaction effect of factors A, C as the average of the difference in the interaction effect A,C at the upper level and the interaction effect of A,C at the lower level. The number of most used interactions of second-order pairs can be determined by the relation (2):

$$I_p = \frac{k * (k-1)}{2} \qquad (2)$$

Where:
IP – the number of pairs of second-order interactions
k – number of factors

Possible variants of interactions of pairs (pairs) of factors are presented in Table 3.

Table 3 Possible variants of interactions of second-order pairs

Number of factors	Factors	Number of factor pairs	Interactions
2	A, B	1	AxB
3	A, B, C	3	AxB, AxC, BxC
4	A, B, C, D	6	AxB, AxC, AxD, BxC, BxD, CxD
5	A, B, C, D, E	10	AxB, AxC, AxD, AxE, BxC, BxD, BxE, CxD, CxE, DxE
6	A, B, C, D, E, F	15	AxB, AxC, AxD, AxE, AxF, BxC, BxD, BxE, BxF, CxD, CxE, CxF, DxE, DxF, ExF
7	A, B, C, D, E, F, G	21	AxB, AxC, AxD, AxE, AxF, AxG, BxC, BxD, BxE, BxF, BxG, CxD, CxE, CxF, CxG, DxE, DxF, DxG, ExF, ExG, FxG

The number of interactions explodes with the increase in the number of factors and their levels, as shown by the relationship. An example of the increase in the number of interactions depending on the number of factors and their levels is shown in Figure 4.

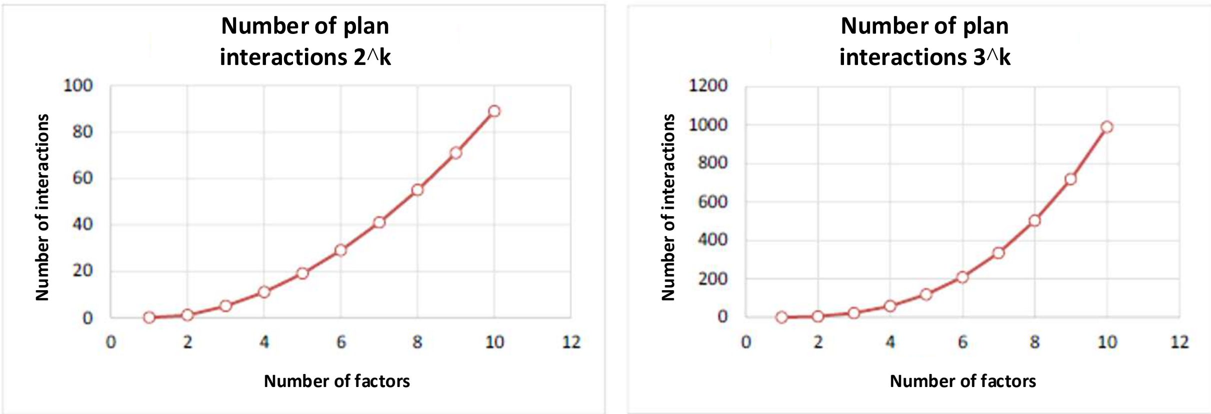

Figure 4 Exploding number of interactions depending on the number of factor levels

With a high number of factors, the experimenter's effort is to reduce their number, i.e. to reduce the number of factors k by the value p. Such reduced plans are then referred to as 2^k-p plans.

The process itself represents the transformation process, which in this case is a black box, so we know (or choose) the values of the inputs and also know how the process responds to changes in inputs (responses, effects). However, we usually do not know the transformation process, i.e. the way in which the studied process turns inputs into outputs, we do not have an exact or approximate representation of it (descriptive model). We are trying to create such a model on the basis of based on the results of experimentation, as shown in Figure 5.

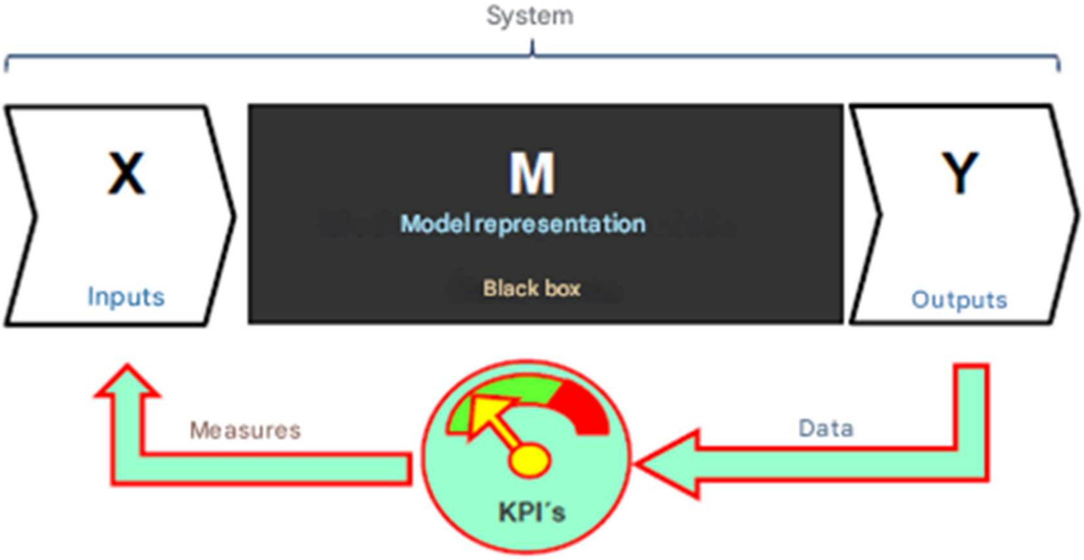

Figure 5 Model representation of the process

What we are looking for in an experiment is an explicit or approximate form (substitute mathematical model) expressions of transformation dependence (3):

$$y = f(x_1, x_2, \dots, x_n) \quad (3)$$

If a process has multiple parameters, we create a mathematical model for each of its parameters. Therefore, if we want to optimize the operation of the production system and the main factors whose effect we want to determine include, for example: the number of operators, the number of mobile robots and the number of workplaces, then what will be changed at the input will be the levels (values) of these factors. At the same time, we will observe in the experiment how the values of responses (parameters) change when the levels of factors change. Let the parameters in this case be, for example: production performance and continuous production time. Then, by experimentation, we will look for two substitute mathematical models, one for the dependence of production output on selected factor levels and the other for the dependence of continuous production time on selected factor levels. If the experiment results in finding replacement models, we can then use them to optimize the process or to predict its future behavior. In the simulation, experiments are carried out using a simulation model. In this case, we will replace the real process with its simplified representation, a simulation model with which we will carry out an experiment. The experiment itself will be carried out as a series of simulation runs (experiments), in which we will change the levels of input factors and monitor the responses of the process to such changes. Based on the known levels of input factors and the observed responses of the process, we can create the required substitute mathematical model of the process. As can be seen from Figure 6, in the process of searching for a substitute model, we try to gradually replace the existing process (black box) with a simplified representation of the process in the form of a dynamic simulation model (gray box). With the simulation model, we perform a set of experiments and, based on the results of the experimentation, we look for a suitable mathematical representation of the process (its model). Experiment planning is therefore a procedure in which we select the appropriate main factories and their levels, select the required parameters (responses), determine the way in which the input factors will be varied and the way in which the results of the experimentation will be evaluated. If there are many input factors and the number of their levels is high, the required number of attempts will be very high and experimentation will be very computationally and time-consuming. Therefore, methods have been proposed to reduce the number of attempts. The plan of experiments (or more simply, the plan) then represents the prescription on the basis of which the individual experiments will be carried out. Such a plan defines the setting of factor levels so that, if necessary, the experimenter is able to estimate the regression coefficients β the descriptive model.

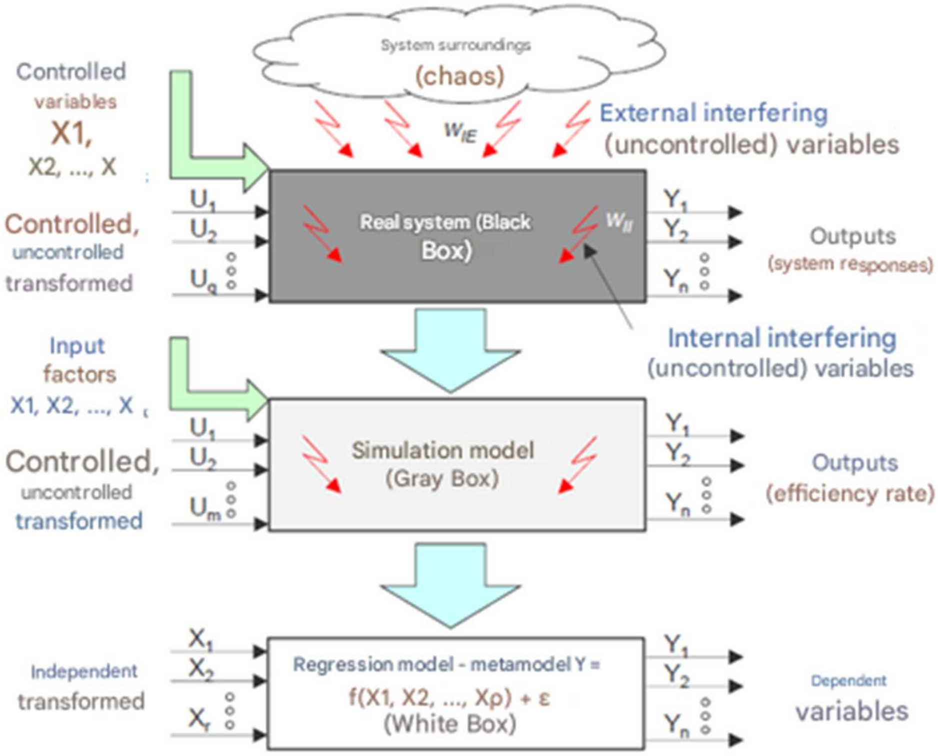

Figure 6 The process of finding a replacement model

4 Discussion and conclusion

The results presented in this study confirm that planned simulation experiments play a key role in optimizing production systems, especially under conditions where a wide range of factors and their interactions need to be investigated. In contrast to the OVAT approach, which examines individual factors in isolation, factor experiments – such as full or fractional factorial plans – offer a more holistic understanding of process changes and allow for systematic detection of the effects of interactions. It is these interactions that are often critical in complex production processes, where several parameters change at the same time.

In addition, careful planning of simulation experiments reduces the risk of incorrect conclusions due to insufficient data volume or confusion of cause and effect. If the input parameters are appropriately divided into controlled and disruptive, interference can be significantly reduced and reproducible results can be obtained. In industrial practice, this brings a direct benefit in the form of a reduction in the time needed to put new products into operation and a reduction in the costs associated with any defective batches. In addition, detecting key factors makes a significant contribution to being able to react more quickly to unexpected situations, such as changes in demand or the supply chain.

Due to the exploding number of interactions with a higher number of factors, fractional factorial plans (2^k-p) are popularly used in industrial practice, which seek a compromise between a minimum number of attempts and sufficient statistical informative value. Such an approach has been shown to help significantly reduce the time of experimentation while providing enough information for decision-making. An important part of this is also taking into account non-Gaussian conditions or different types of random variable distributions, which allows for better adaptation of the simulation model to real production conditions. Based on the analyzed approaches to the planning of simulation experiments, it can be concluded that the effective use of simulation and carefully designed experiments can bring significant improvements in production, whether it is shortening lead times, reducing the number of defective products or better use of resources. In industrial applications, it is necessary to place particular emphasis on the correct identification of decisive factors, thoughtful definition of input levels and adequate analysis of output statistics. This is the only way to achieve high reliability and practical usability of the results.

At the same time, the acquired knowledge points to the importance of further research in the field of the application of advanced optimization methods in combination with simulation technologies that can solve increasingly complex problems. In the future, an even more intensive connection between simulation, optimization and digital technologies can be expected, which will further improve and accelerate the process of designing and managing production systems.

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