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Dynamic Modelling and Simulation of Production Processes

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Abstract

The aim of this paper is to analyse the possibilities and benefits provided by the use of the modelling and simulation method in production management with particular emphasis on System Dynamics (DS) and Discrete Event Simulation (DES). The presented analysis led to the conclusion that the modelling and simulation method, regardless of the approach used, should be one of the most important methods supporting production management. Its primary strength lies in enabling the tracing of complex processes, which in reality last for several weeks, months, or years, within a few minutes, and consequently, testing multiple decision variants before implementing them. However, it should be noted that building a simulation model is time-consuming and requires extensive knowledge of the process under study, mathematical skills, and a good understanding of the software used to carry out the simulation project.

Keywords:

Computer Simulation; Modeling; System Dynamics; Discrete Event Simulation; Production

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1. Introduction

The organizational structure of the production process is incredibly complex, with challenges arising at every stage of a product's life cycle. From design, through technical and organizational preparation, manufacturing itself, marketing, sales, after-sales service, to disposal – each of these phases requires quick decision-making while simultaneously predicting their consequences. In the face of such a dynamic environment, it becomes essential to employ appropriate methods to support this process. Classical analytical methods often prove insufficient due to the multitude of possible solution variants and their complexity. In this context, modeling and simulation emerge as potentially effective tools for supporting decision-making at various levels of production management.

The aim of this paper is to analyse the possibilities and benefits of using the modelling and simulation method in production management by explaining its essence and types and presenting examples of production process models constructed using two simulation approaches—Discrete Event Simulation (DES) and System Dynamics (DS).

The remainder of the article is structured as follows: next section discusses the fundamental assumptions and significance of modeling and simulation in production management. The following two sections are devoted to a presentation of two key simulation approaches: Discrete Event Simulation, and System Dynamics - with examples of its applications in modeling production processes. In the next section comparison of DES and DS approaches is conducted, highlighting their differences and similarities. The last section contains key findings.

2. The essence of modeling and simulation of the production process

Modeling involves the construction of a model that represents the most significant characteristics of the studied or designed object from the perspective of the task it serves in a given reality or abstraction (Durlik, 2000).

The literature discusses various models of the production process (Matuszek & Kurczyk, 2013). Among the most universal and widely used at all levels of management are schematic models (block diagrams, business process maps in various notations, e.g., IDEF, BPMN, UML, etc.). Their role is primarily limited to the static analysis of the problem. These models represent the production process, its structure, elements, relationships between them, and the functioning of the production system; however, they do not allow for determining the consequences of decisions made. For this purpose, computer simulation models are used (Vasudevan & Devikar, 2011). These belong to the group of symbolic models, where reality is represented using symbols and mathematical relationships.

A computer simulation model captures the logic of the behavior and the interrelationships between individual elements of the studied production process, as well as the data that represent the characteristics of these elements. The course of the process can be graphically represented through animation, and after conducting a simulation experiment, the results are obtained in the form of charts, reports, or a set of statistics describing specific elements of the process. The content and form of the presentation of these results largely depend on the applied simulation approach. The results of the experiments can serve as a basis for making decisions regarding changes that need to be made in the existing process (e.g., the number of machines, assembly stations, product range, warehouse capacity, etc.) to achieve a desired goal (e.g., increasing production efficiency, reducing manufacturing costs, or shortening the production cycle).

According to the literature (Jovanovski et al., 2012; Matuszek & Kurczyk, 2013; Tako & Robinson, 2010), two simulation approaches are well-suited for modeling and simulating the production process, for which specialized computer tools and simulation languages have been developed. These are:

- Discrete Event Simulation (discrete simulation) – e.g., GPSS, Arena, eMPlant, AutoMod, Enterprise Dynamics, FlexSim,
- System Dynamics (continuous simulation) – e.g., VenSim, PowerSim, iThink.

Currently, many simulation tools available on the market allow for conducting both continuous and discrete simulations, such as Extendsim (www.extendsim.com) or AnyLogic (www.anylogic.com/).

3. Discrete Event Simulation (DES)

In Discrete Event Simulation, the studied process is modelled as a sequence of events, with state changes occurring at specific points in time, at the moment certain events take place. Between these events, the state of the process does not change. The process is seen as "jumping" from one state to the next, similar to how frames in an animated film change.

DES models are those that reflect the flow of certain units within the studied process. The task of the modeller is to define the state variables that are relevant from the perspective of the study's objective, the events that cause changes in these variables, and the logical relationships between them (Rabelo et al., 2005). A very communicative and widely used method for the formal description of discrete simulation models is through flow diagrams or activity networks. The type of graphical notation typically depends on the simulation tool used to create the model. The theoretical foundations and detailed principles of modelling and simulation within the DES framework have been presented in numerous publications, e.g., (Banks, 2010).

To illustrate the application of the discussed simulation approach in studying a production process, a model is presented based on Grigoryev (2012, pp. 22–74). The flow diagram for this model is shown in Figure 1. It reflects the operations of a production department in a manufacturing company where a product is produced—in this specific example, automatic washing machines—comprising two pre-manufactured components. These components are delivered to the modelled department according to an exponential distribution, after which a conveyor transports them to the assembly station. After assembly, the products are sent for packaging, and then loaded in batches onto trucks and transported to customers.

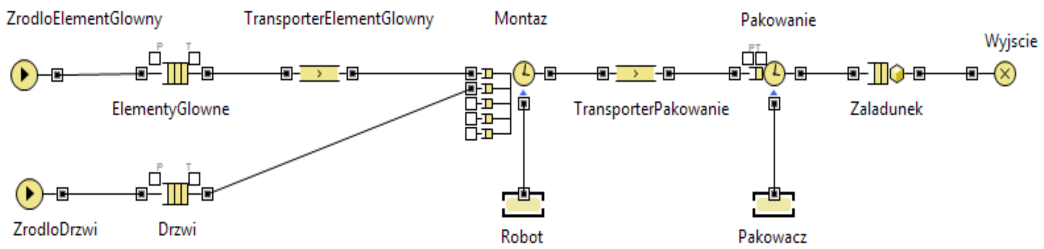

Figure 1. Flow diagram of the production process model in AnyLogic simulation package notation.

Source: own elaboration based on (Grigoryev, 2012)

This model effectively demonstrates how discrete event simulation can be used to replicate and study the logistics and production flow of a manufacturing unit, from the arrival of components to the final delivery of products to customers.

An example of the visualization of the course of an experiment carried out with the use of the AnyLogic simulation package and the presentation of the results is shown in Fig. 2.

Figure 2. Example of the visualization of the experiment process and presentation of results using the AnyLogic simulation package.

Source: own elaboration based on (Grigoryev, 2012)

During discrete event simulation, various statistics and performance metrics of the observed process are calculated. These typically include average time delays, service station throughput, average downtime related to, for example, machine maintenance and repairs, and machine failure rates, among others. Analysing these metrics helps identify weak points in the studied production process and enables the development of scenarios for improvements aimed at optimizing the process.

4. Continuous Simulation – System Dynamics

System dynamics (SD) is a continuous simulation method developed in the late 1950s by J. W. Forrester and his colleagues at the Massachusetts Institute of Technology (Forrester, 1958). A distinctive feature of continuous simulation is the use of continuous functions in the formal description of the characteristics of the system's state variables, as well as continuous or quasi-continuous functions in describing the phenomenon of time flow. In continuous simulation, the state of the system is typically determined using a system of differential equations as a function of simulated time.

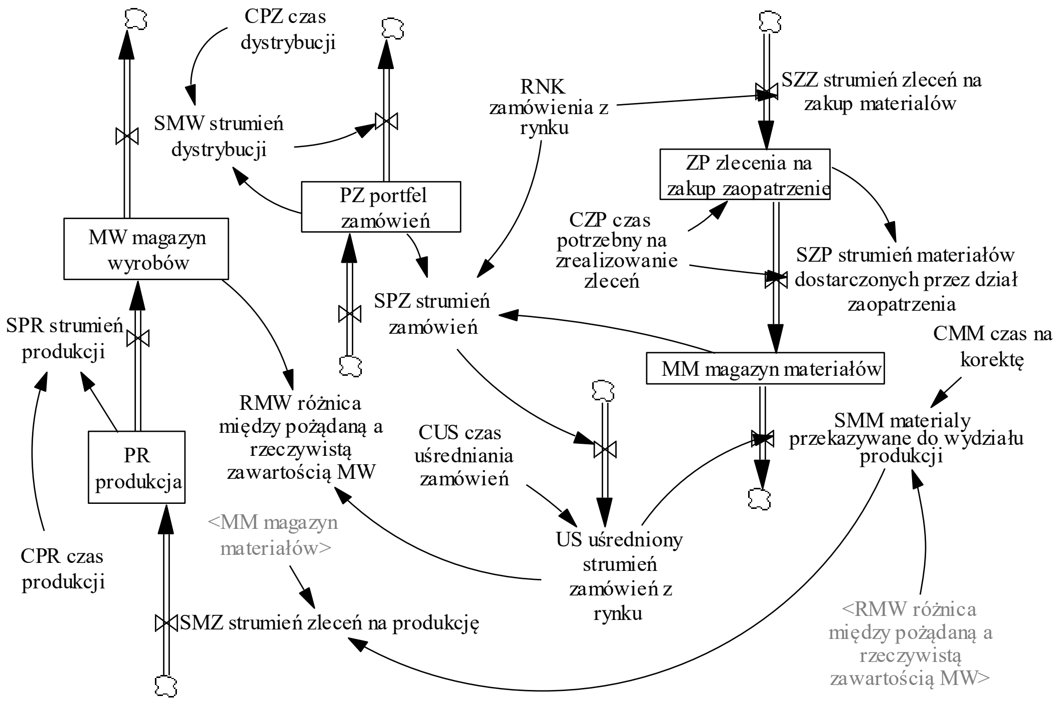

Figure 3. Structural diagram of the production process model in the notation of the Vensim simulation package.

Source: (Łatuszyńska, 2004)

Creating a system dynamics model requires identifying causal relationships that form feedback loops between the elements of the studied system, which determine the system's behaviour (Sterman, 2010). The structure of a system dynamics model is expressed using two basic types of variables: so-called levels and flows. The modeller employs a specific graphical notation, which varies slightly depending on the software tool used. The theoretical foundations and detailed principles of modelling and simulation within the system dynamics framework have been presented in numerous publications, including (Łatuszyńska, 2008).

To illustrate the application of the discussed simulation approach in studying a production process, a model is presented based on (Łatuszyńska, 2004). This model simplifies the logic of a manufacturing company's operations. The structural diagram of the model is shown in Figure 3, which represents five key departments of the production company, depicted as levels: order portfolio, supply, materials storage, production, and finished goods storage. The simulation calculations, the results of which are presented through a sample chart in Figure 4, were conducted using the Vensim software package.

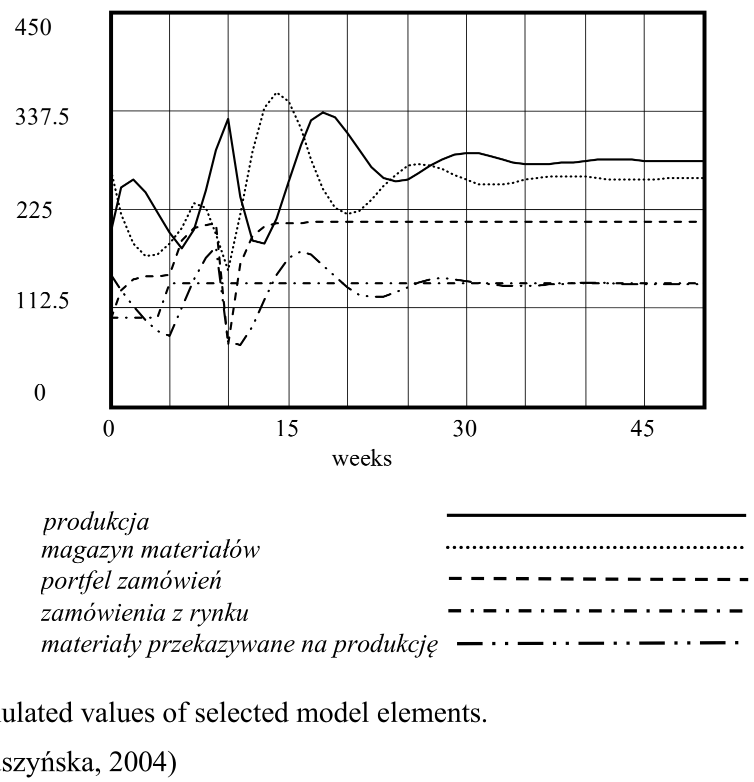

Figure 4. Simulated values of selected model elements.

Source: (Łatuszyńska, 2004)

Due to the high level of aggregation of variables in a system dynamics model, the results obtained from experiments primarily allow for the analysis of the stability of the studied system (process) over the long term. They indicate trends in the behavior of the elements represented in the model but do not provide precise point forecasts, visualize individual operations, or determine their statistics. Instead, they enable the verification of various decision hypotheses, particularly regarding the consequences of implementing alternative production strategies related to material supply for production and the system's response to disturbances caused by various market signals.

5. Comparison of Discrete Event Simukation and System Dynamics Approaches

Simulation models, both DES and SD, are typically built to facilitate the understanding of the behavior of the studied system (process) over time and to compare the results of experiments showing its functioning under different conditions. However, from a technical perspective, they represent different approaches. The discussion regarding their comparison has been present in the literature since the mid-1990s. Notable contributions to this discussion were made by Ruiz-Usano et al. (1996), Crespo-Marquez et al. (1993), Sweetser (1999), and Brailsford and Hilton (2001). The topic was also addressed by Morecroft and Robinson (2006, 2014) and Tako and Robinson (Tako & Robinson, 2009b, 2009a, 2010), and in 2014, a monograph presenting various perspectives on the nature of both simulation approaches was published (Brailsford et al., 2014). A more detailed and organized comparison (across more than thirty categories) is provided in the work by Chahal and Eldabi (2008). A synthetic summary of both approaches, resulting from the review of the aforementioned literature, is presented in Table 1.

Table 1 Comparison of Discrete Event Simulation and System Dynamics approaches

Discrete Event Simulation	**System Dynamics**
Problem	
Investigating the impact of randomness on the system/process	Investigation of the impact of internal feedbacks on the system/process
Level of detail	
High level of detail in system/process representation	Low level of detail, aggregation of system/process elements
Level	
Operational	Strategic
Methodology	
Process Orientation	System orientation
Philosophy	

Discrete Event Simulation	System Dynamics
Randomness	Feedback

Source: (Jovanovski et al., 2012, p. 137)

Generally, in SD, the focus is primarily on understanding the functioning of the system (process) resulting from its internal feedback structure. This structure is evident in the representation of the SD model and is expressed through a system of differential equations, which are often nonlinear. Randomness is rarely considered; if it is, it is simplified and often added only after conducting experiments without random disturbances. Conversely, modelers using DES emphasize randomness without much concern for the effects of feedback loops. As a result, those employing SD view the feedback structure as the main source of system behavior, while those using DES perceive randomness as its fundamental cause (Brailsford et al., 2014, p. 193). In discrete event simulation, state changes occur at irregular, discrete time steps, while in SD, state changes are continuous, calculated at regular, small time intervals of equal length (Tako & Robinson, 2012).

All authors emphasize that the SD approach necessitates analyzing the studied system as a whole, leading to a high level of aggregation in the model, while DES requires detailed data for modeling. There is also a general consensus that SD is more suitable for modeling at the strategic level, whereas DES is better for operational and tactical levels.

In summary, it can be stated that DES and SD are based on quite different modeling philosophies. The similarities between these two approaches seem to end at the point that both aim to reflect the functioning of the system over time.

6. Key Findings and Conclusion

The modelling and simulation method is one of the key techniques supporting production management. Its fundamental strength lies in its ability to dynamically trace all phases of the production process (from product design to disposal), which can sometimes span several years, within just a few minutes. This allows for the testing of various decision-making scenarios related to process organization before they are implemented.

However, it is important to remember that modelling and simulation, regardless of the approach used, are not optimization methods or automatic solutions for problems. They are primarily experimental methods that help decision-makers answer questions such as: what will happen if..., where are the weak points in the designed or implemented production process, and what irregularities might arise under a specific process variant.

Before employing this method, it is necessary to decide which simulation approach to use, considering that system dynamics is more suitable for modelling at the strategic level, while discrete event simulation is better for operational and tactical levels.

Moreover, it should be recognized that building a simulation model is time-consuming and requires extensive knowledge of the studied process, as well as mathematical skills and a good understanding of the software used for the simulation project. Nevertheless, the rapid advancement of computer technology and increasingly user-friendly simulation tools enable the broader application of modelling and simulation methods in production management.

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